Title: A memory-integrated artificial bee algorithm for heuristic optimisation

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A MEMORY-INTEGRATED ARTIFICIAL BEE ALGORITHM FOR HEURISTIC OPTIMISATION

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A MEMORY-INTEGRATED ARTIFICIAL BEE ALGORITHM FOR HEURISTIC OPTIMISATION

by

T. BAYRAKTAR

A thesis submitted to the University of Bedfordshire in partial fulfilment of the requirements for the degree of Master of Science by Research

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ABSTRACT

According to studies about bee swarms, they use special techniques for foraging and they are always able to find notified food sources with exact coordinates. In order to succeed in food source exploration, the information about food sources is transferred between employed bees and onlooker bees via waggle dance. In this study, bee colony behaviours are imitated for further search in one of the common real world problems. Traditional solution techniques from literature may not obtain sufficient results; therefore other techniques have become essential for food source exploration. In this study, artificial bee colony (ABC) algorithm is used as a base to fulfil this purpose. When employed and onlooker bees are searching for better food sources, they just memorize the current sources and if they find better one, they erase the all information about the previous best food source. In this case, worker bees may visit same food source repeatedly and this circumstance causes a hill climbing in search. The purpose of this study is exploring how to embed a memory system in ABC algorithm to avoid mentioned repetition. In order to fulfil this intention, a structure of Tabu Search method -Tabu List- is applied to develop a memory system. In this study, we expect that a memory system embedded ABC algorithm provides a further search in feasible area to obtain global optimum or obtain better results in comparison with classic ABC algorithm. Results show that, memory idea needs to be improved to fulfil the purpose of this study. On the other hand, proposed memory idea can be integrated other algorithms or problem types to observe difference.

DECLARATION

I declare that this thesis is my own unaided work. It is being submitted for the degree of Master of Science by Research at the University of Bedfordshire.

It has not been submitted before for any degree or examination in any other University.

Name of candidate: Signature:

Date:

LIST OF ABBREVIATION AND ACRONYMS

ABC : Artificial Bee Colony

BF : Best Fit

BFD : Best Fit Decreasing

BP : Bin Packing

Et al : And others

FF : First Fit

Fig : Figure

MEABC : Memory Embedded Artificial Bee Colony

NF : Next Fit

NP : Non-deterministic Polynomial

STTL : Short Term Tabu List

WF : Worst Fit

LIST OF SYMBOLS IN EQUATIONS

H : Hessian Matrix

∂² : Second Partial Differential

X : Solution Value

U : Upper Bound for a Solution Parameter

L : Lower Bound for a Solution Parameter

V : Possible Solutions in Neighbourhood Area of Current Solution Value X

Ø : Random Real Value Between -1 and +1

Abs : Absolute Value

P : Probability Value for a Solution Value X to be Chosen

∑ : Summation

SN : Size of the Initial Population

Rand : Random Real Value between 0 and +1

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Chapter 1: Introduction

Problem solving has been a challenging area of research for some time. Deterministic methods which are used for searching for global optimum tend to obtain an exact solution which usually requires too much time, money and manpower. Prior target for any establishment is optimising the requirement for these three main resources. More importantly, they usually disregard parameters of problem sets and consider rather abstract models in problem solving whereas, in real life, most of the problems do not require exact solutions due to the difficulties obstructing implementation of the exact solution. Thus, the solutions should be rather flexible to tolerate sudden changes in circumstances. Heuristic search methods are more suitable for solving real life problems because they do not require an exact solution. They just propose a variety of approaches to approximate the exact solution.

A heuristic search method requires the following steps. Firstly, the problem should be defined with a finite set of search space, decision variables, objective function, and feasible function to be able to obtain optimum value of the objective function. Secondly, a *neighbourhood function* should be defined to search through a local *neighbourhood* within the search space. A search method is designed to find a feasible solution within the neighbourhood of a feasible solution area and to make a decision whether or not to move to the new solution by applying one of the heuristic search algorithms such as Hill-Climbing, Simulated Annealing, Tabu Search, Genetic Algorithm, Artificial Bee Colony Algorithm.

In this study, one of the aforementioned heuristic methods is applied for a kind of combinatorial non-deterministic polynomial (NP)-hard problem known as a bin packing problem, which aims to fill bins with different objects due to the dimensional relation between them.

The main purpose of bin packing problems is using an area for stocks in a facility as small as possible to reduce the stocking cost. In order to avoid area wastage, firstly we need to define object and repositories such as bin, container. There are many variations of this problem, such as 1 or 2 or 3-D packing problems, packing by weight or cost, loading trucks by weight. There are not only induction based packing problem examples. There are also many deduction based packing problems such as cutting stock problems.

Researchers may need to answer some questions such as if applied algorithm is compatible with tackled problems (deterministic or non-deterministic) or not and if they really need to develop an algorithm or not. For example deterministic problems may not require a kind of developing algorithm process due to their structure. On the other hand, they need to consider and define requirements of tackled problems. In this way, they can find suitable algorithms for the solution of tackled problems. In this study, we also considered classic algorithms with their performance and results for comparison with developed algorithms.

1.1 Collective Behaviours and Swarm Intelligence

Most creatures, especially tiny sized animals, have to be in cooperation with the same gender in nature in order to overcome various difficulties due to their handicaps such as their weaknesses in comparison with other genders and stocking problems for foraged food. If some members of any gender among creatures come together to benefit from each other's capacity or energy for any purpose, this form is called a "*swarm*". Swarms in nature have rules to maximize the benefit from resources and protect the reasonable condition of the swarm system.

Mankind has been inspired by nature to make several developments and innovations throughout history. Optimisation researchers are also inspired by swarm intelligence and imitate this to develop several algorithms to obtain or approximate the best solutions for some problems they tackle. Basically, researchers apply techniques based on swarm intelligence step by step. In this study, we use techniques especially based on insect (bee) behaviours and try to understand the intelligence behind these behaviours. Insects apply complex algorithms to overcome problems in nature and this speciality shows us an alternative way about how to reach an optimum solution. All studies about swarm behaviours and intelligence reveal the wonderful systems in creatures' lives. As aforementioned in this study, bee swarm intelligence and behaviours will assist us in developing an algorithm.

Artificial Bee Colony (ABC) Algorithm is a bio-inspired population-based heuristic search method simulating behaviours of honey bees. The algorithm is a recently implemented heuristic algorithm which briefly works as follows: Initially, half of the colony is recruited as active bees and the other half as the onlooker bees. Active bees are responsible for foraging and gathering information to share with onlooker bees. When the amount of food, which is provided by active bees, decreases to an insufficient level, the active bees proceed to forage without sharing information or abandoning the food and become scout bees. Based on the information on existing food sources shared by active bees, inactive bees may also start foraging.

1.2 Proposed Algorithm

The main disadvantage of the artificial bee colony algorithm is that bees search for a food supplier and memorize a resource until they find a better one. In this situation, they may visit the same resources repeatedly and it is a kind of hill climbing which is known as one of the main threats during optimum searching because in case hill climbing fails in local optimum curve we would never reach the main goal of search. In this section, we will describe what stimulates us to develop a hybrid algorithm and how to overcome the threat mentioned above.

1.2.1 *Aim and Objectives*

The aim of this research is to investigate how a memory mechanism can be embedded in bee algorithms so that the bee colonies are enabled to remember their past experiences, and be sensitive to search within other neighbourhoods. The main reason for using a memory mechanism is that, search for global optimum may fall in a local optimum and may not escape from there. This condition is a typical example for fail of hill climbing in a local optimum. For this purpose the tabu list idea is borrowed from the tabu search algorithm [1] and is integrated into Bee algorithms to help improve the search performance. In this way, we may constrain the search not to test solutions in local optimum and search may escape from there by testing other solutions from outside of local optimum.

The objectives are:

- To find out if a memory can be integrated into bee algorithms
- To investigate how a memory can improve the efficiency of a bee algorithm
- To find out if a tabu list is a good memory mechanism for bee algorithms
- To reveal the circumstances in which memory can work better with bee algorithms
- To demonstrate if memory-embedded bee algorithms can solve one-dimensional bin-packing problems better.

1.2.2 *Methodology*

A classical bee algorithm is considered as the starting point of this research, where it is applied to a one-dimensional bin-packing problem. The behaviours of such an algorithm will be revealed through a literature search as well as experimental study. It will be focused on how quick such a bee algorithm traps local optima and subject to which circumstances. Once this step is completed, the memory mechanisms will be investigated to make the bees more conscious and able to use past

experiences. Tabu search is one of the metaheuristic algorithms that use memory mechanisms to diversify its search [2]. It requires harvesting neighbour solutions and moves from the current solution to the best harvested ones subject to a memory mechanism. The memory mechanism is called a tabu list, which is dynamically updated throughout the search. The main idea of a tabu list is that once a move is decided it is immediately considered as a tabu move for a period of time, and then is released. This restriction is expected to help bees included in the search mechanism of bee algorithms to be more decisive in their search. There will be further investigation on how this idea would incorporate with bee algorithms for better performance in solving a one-dimensional bin-packing problem. An extensive experimental study will be conducted to measure the performance of the variants of this integration and to set up parametric configuration of the algorithms.

The rest of this study is classified into four other chapters. Brief descriptions of the chapters are provided below to make clear how to develop the proposed algorithm of the study. Besides, a comparison between classic algorithms and the proposed algorithm is also provided to evaluate developed algorithm performance.

Chapter 2: This chapter includes all background information about the study, referring to reputable and reliable sources such as Applied Soft Computing, Information Sciences, European Journal of Operational Research and other scientific community web sources.

Chapter 3: In this chapter, a proposed solution with necessary techniques and algorithms is introduced after explanation of classic algorithm implementations in chapter 2 because the new algorithm is built on this theme. Both classic and newly developed algorithms are analyzed to present the fitness performance difference between them.

Chapter 4: After description of classic algorithms and introduction of the proposed algorithm in chapter 2 and chapter 3, they are implemented on several 1-D bin packing problem variable databases. In this study, MATLAB 2012 software is used for implementations. After implementations of every single database with different algorithms, results belonging to classic algorithms, modern algorithms and the newly developed algorithm are compared with discussion about testing techniques.

Chapter 5: The final chapter will conclude with a brief discussion about the findings of the study and a summary of the entire study with possible future works.

Chapter 2: Literature Review

Optimisation research has been a rapidly growing area of engineering, mathematical science, computer science and management for the last few decades. The main reasons for this growth are the high cost of wastage of resources which have some limitations for use and rising demands. All optimisation problems are about minimizing the wastage to benefit resources completely and maximizing the output of processes we tackle. Inputs and outputs of processes have different limitations which lead researchers to propose ideas about finding the best solution to these different processes; in other words, problems in a feasible area that are defined by these limitations.

Before solving a problem there should be a clear definition of it because the characteristics of problems lead the way to possible solutions. After definition, the path to solve the problems, in other words methods/algorithms, needs to be applied to find an optimum or near optimum solution for the system.

Researchers expect a few unique characteristics, which are aligned respectively as five-bullet-point, from applied optimisation methods/algorithms:

- Tackled methods/algorithms would not fall into local optimum
- Competitive computational time in comparison with others
- They could be implemented in general purpose computer algebra systems
- They could be applied to a wide range of deterministic or non-deterministic problems
- They could be combined with other methods/algorithms to increase the efficiency [3]

Problem sets firstly can be divided due to their convexity characteristics in the optimisation area.

If the feasible area/set where variables of the problem set are placed has a convex shape, in which any two variables can be connected directly without the line between them exceeding the field, it is called a convex set and searching for the optimum in the convex set is called convex optimisation.

If one of the variable pairs cannot be connected directly as defined above, it is called a non-convex set and the name for searching for the optimum in this set is called non-convex optimisation. The shapes of the convex and non-convex set are shown as in Fig. 1.A and Fig. 1.B. [57]

In addition to the problem of subdivision due to their convexity characteristics, there are two kinds of problems due to whether they tackle decimal or integer variables which are discrete and continuous problems [59].

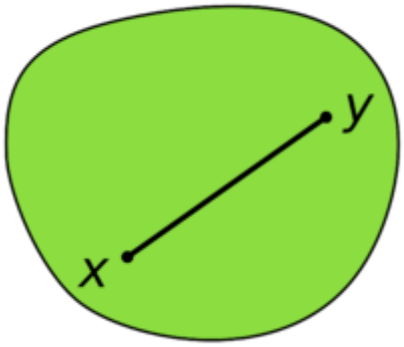


Fig. 1.A: Convex Set

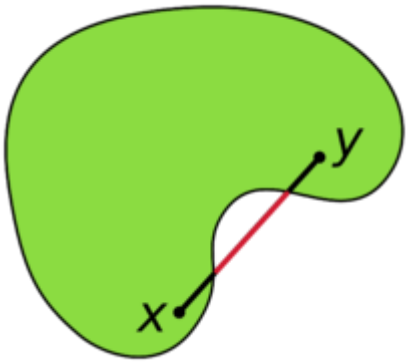


Fig. 1.B: Non-Convex Set

While tackling continuous problems, the solution searching (feasible) area for optima consists of real numbers. In this circumstance, any solution can be found in the whole searching area. This means that, obtaining a better solution has a high possibility rate with all facets of the searching area. Mathematical optimisation problems are such a good example of continuous problems [59].

On the other hand, while tackling discrete problems, the feasible area consists of integer numbers, so the solution is also an integer. This circumstance restricts the search in feasible areas and may give us a lower possibility of obtaining a better solution which can be between two integer solutions and it is unacceptable for discrete problems. For example, combinatorial optimisation problems are a branch of discrete problems [59].

There is another and final subdivision for optimisation due to linearity characteristics of objective functions. If none of the variables of the objective function are quadratic, polynomial or high degree, this objective function is called a linear function. Otherwise, it is called a non-linear function. Fig.-2 shows the subdivision of optimisation problems by characteristics [5].

After the definition of the type of tackled problems, researchers search for the easiest and the best way to solve problems and find the optimum/optima. Many researchers have been trying different and better optimisation techniques to obtain the best solutions or approximate them. Mainly, there are two kinds of research technique to converge to the optimum/optima which are deterministic optimisation (mathematical programming) and heuristic optimisation [4].

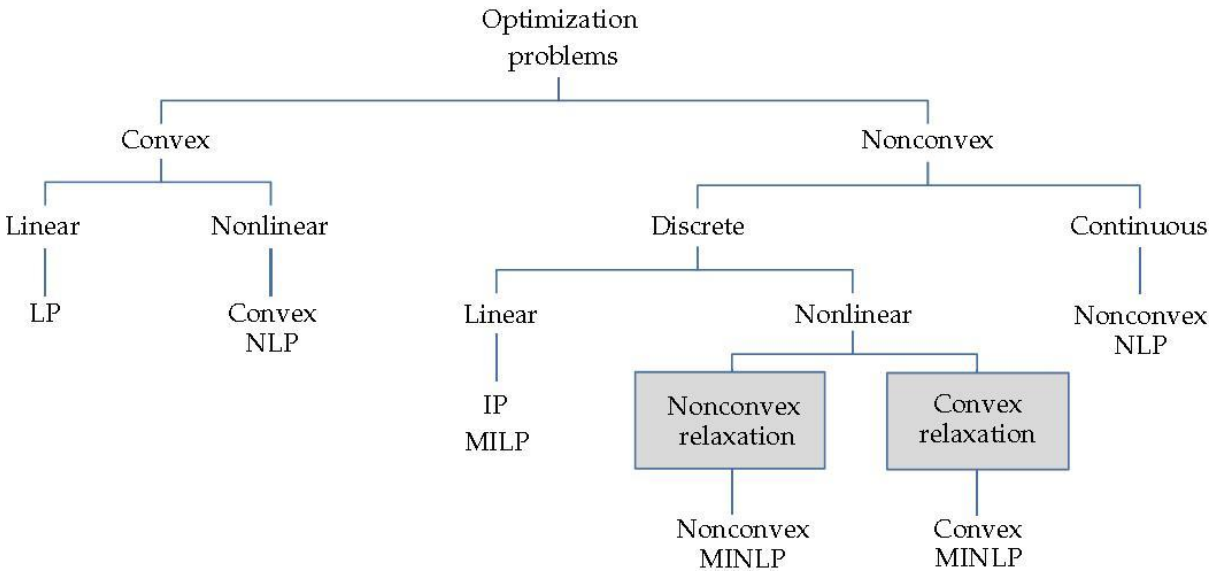


Fig. 2: Branches of Optimisation Problems

LP: Linear Programming, **NLP:** Non-linear Programming, **IP:** Integer Linear Programming, **MILP:**Mixed Integer Linear Programming, **MINLP:** Mixed Integer Non-Linear Programming [5].

2.1 Deterministic Optimisation

Mathematical programming or deterministic optimisation is the classical branch of optimisation algorithms in mathematics. The algorithms for obtaining the best possible solutions which are heavily related to linear algebra comprise the deterministic optimisation. These algorithms are based on the computation of gradient, and in some problems also of the Hessian. Deterministic optimisation has some remarkable advantages alongside its drawbacks. One of the aforementioned advantages is the convergence to a solution which would be much faster than stochastic/heuristic optimisation algorithms in comparison because applying the deterministic algorithms does not require the amount of iterations/evaluations as stochastic/heuristic algorithms do to reach the solution. When deciding which algorithm or function would be tackled by researchers, the results of necessary convergence time for the optimum solution should be measured for comparison between them. In some cases an algorithm may obtain better results than others; however, time requirements for convergence can be too much so researchers look for economic value in the algorithm they tackle.

Deterministic algorithms are commonly based on complicated mathematical formulations and it means that the results are never obtained by randomisation and they obtain the same solution in

each run. This fact could be true also for stochastic/heuristic algorithms, however these algorithms are based on randomisation and they may obtain different solutions in each run [4].

Most researchers find heuristic approaches more flexible and efficient than deterministic methods which commonly take advantage of analytical properties of the problem; however, many optimisation problems consist of complicated elements beside their analytical aspects. The quality of the obtained solutions may not always be sufficient. One of the stochastic/heuristic approach drawbacks is reduction in the probability of finding a global optimum while searching in big size problems. Conversely, deterministic approaches can provide general tools for solving optimisation problems to obtain a global or approximately global optimum which is a solution that a function reaches highest or lowest value, depending on problem, by using it [5].

Many different fields in optimisation problems would apply to deterministic optimisation. Skiborowski et al. [6] developed a hybrid optimisation approach based on one of the necessary attributes of applied methods/algorithms which is combinational flexibility in process design. They also applied the traditional deterministic optimisation algorithm as a second phase using the results data of the first phase, which is processed by an evolutionary algorithm in a case study. Marcovecchio and Novais [7] developed a mixed integer quadratic programming problem (MIQP) model with a deterministic optimisation approach and apply it to the unit commitment (UC) problem which has NP-Hard characteristics. In [7], the unit commitment problem is applied for a case study about reliable power production as a most critical decision process for a large number of interacting factors. Trindade and Ambrosio [8] proposed one of the deterministic optimisation methods that can provide some qualified estimates for segment characteristics in the latent segment model when only aggregate store level data is available. In [8], the storage system works dynamically, so they test the Sequential Quadratic Programming (SQP) method which is a branch of deterministic optimisation and accept it as a model fit for estimation in the case study. Sulaiman et al. [9] used a deterministic method approach to improve the power density of the existing motor used in hybrid electric vehicles (HEV) and they implement the proposed deterministic method on hybrid excitation flux switching motor (HEFSM) as a candidate.

Bin packing problems, the main theme of this study, are also applicable for deterministic methods. Valéiro de Carvalho [10] compared several linear programming (LP) formulations for the 1-D cutting stock and bin packing problems via different algorithms. Carvalho used results from experiments belonging to the mentioned algorithms to analyze characteristics and determine the best algorithm for tackled problems.

Deterministic method/algorithm is based on mathematical calculations and there is no place for arbitrary chosen variables to make the objective function optimum. Despite all the definitions about the advantages of deterministic methods/algorithms expressed above there are some backward aspects for it. In real world problems, systems are commonly dynamic and every single component of systems can change simultaneously over time. Each change for characteristics of components makes the output of systems also change. In this case, a new output of the system should be calculated repeatedly according to new data. Besides, calculations for deterministic models may not be easy or flexible. In this situation, the calculation takes extra time in comparison with others and time wastage is not acceptable in any sector.

We explain the reason why the calculations for deterministic methods sometimes are not easy in the next section. All these facts lead us to search for a new flexible and easy way to save the outputs of systems as much as possible.

2.2 Calculation Difficulties in Newton Search Method

Newton's Method which is a commonly applied deterministic method and its improved forms such as Quasi-Newton and BFGS Formula are based on the idea of approximation of objective function *f* around the current solution by a *quadratic* function and then location of the quadratic function minimum. All these methods work with Hessian Matrix in which an objective function is twice differentiable, which is typically the case for the smooth functions occurring in most applications; the second partial derivatives can tell us more about the behaviour of the function in the neighbourhood of a local solution and formulation of Hessian would be complicated in multi-dimensional problems [60].

The Hessian Matrix formula is shown for an n-variable objective function.

$$H(f) = \begin{bmatrix} \frac{\partial^2 f}{\partial x_1^2} & \frac{\partial^2 f}{\partial x_1 \, \partial x_2} & \cdots & \frac{\partial^2 f}{\partial x_1 \, \partial x_n} \\ \frac{\partial^2 f}{\partial x_2 \, \partial x_1} & \frac{\partial^2 f}{\partial x_2^2} & \cdots & \frac{\partial^2 f}{\partial x_2 \, \partial x_n} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial^2 f}{\partial x_n \, \partial x_1} & \frac{\partial^2 f}{\partial x_n \, \partial x_2} & \cdots & \frac{\partial^2 f}{\partial x_n^2} \end{bmatrix}. \quad (1)$$

Even searching via deterministic methods has some advantages such as convergence speed, starting with a closer point to optimum and constant search results; there are also some backward aspects to applying them. Basically, there are some types of problem such as Non-deterministic Polynomial-time (NP) not eligible for applying to deterministic methods based on Newton's Method Search and its improved forms.

Even though deterministic methods are very useful especially for analytical problems, basic calculations for deterministic methods may have a high cost because of time wastage and calculation cost. Besides, there is a big risk of falling with the local optimum and hill climbing while searching for a global optimum. This means that searches for the global optimum may be misled and so, researchers may not benefit from the global optimum which also means extra cost.

In case researchers face the disadvantages of applying deterministic methods, another way should be sought to beat the hill climbing and to find the global optimum or approximate it better than deterministic methods.

In the next section and further, we will describe and apply heuristic methods as an alternative way to searching by deterministic methods.

2.3 Heuristic Optimisation

In recent decades, tackled optimisation problems have been getting more difficult or impossible to solve by applying the usual optimisation algorithms such as deterministic methods, which have been replaced by several heuristic methods and tools [11].

Heuristic algorithms are criteria and computational methods which decide on an efficient way among alternative methods to reach any goal or solution. These algorithms' approximations to the global optimum are not provable. Heuristic algorithms have approximation attributes but do not guarantee the exact solution unlike deterministic algorithms that guarantee a solution near to the global optimum. Basically, heuristic algorithms are inspired by nature's behaviour such as bee and ant colonies because: creatures' mechanisms are too complicated and cannot be explained by mathematical formulations, so this condition fits problems which are not eligible to be solved by mathematical based methods. There are many reasons for applying heuristic algorithms.

Firstly, there may not be an available method among traditional algorithms to find an exact solution for the tackled optimisation problem such as NP-hard. In this case, researchers should find a new suitable method for this kind of problem.

Secondly, heuristic algorithms can be more helpful because they are not based on complicated formulas unlike deterministic algorithms. Besides, heuristic algorithms are suitable to apply as a part of different algorithms to improve their efficiency for searching for an exact solution; however, this advantage is not easy to implement on deterministic algorithms.

In addition, mathematical formulation-based deterministic algorithms usually disregard the most difficult aspects (which aim and boundaries, which alternatives can be tested, how to collect problem data) of real world problems. If the tackled deterministic algorithm uses incorrect parameters it may find a solution much worse than a heuristic approach. Heuristic algorithms can tolerate incorrect data because they are not based on mathematical formulations; therefore, heuristic methods are more flexible than deterministic methods.

Despite all these advantages of heuristic algorithms, there are some criteria to determine them as an applied method instead of a deterministic method because optimisation problem characteristics determine which method is useful or not. Criteria about evaluation of a heuristic method are aligned as:

- Obtained solution quality and convergence time are really important criteria for making decisions about the efficiency of any heuristic algorithm. Therefore, a qualified algorithm should have changeable parameter sets which are able to be compared easily according to their calculation cost and obtained solution quality attributes. In other words, the connection between obtained solution quality and convergence time should be considered.
- The applied algorithm should be applicable commonly and its components should be clear to understand the system easily. In this condition, even though there is little information about problem characteristics, the attributes mentioned above allow the algorithm to be applied easily in new areas.
- Heuristic algorithms involve flexible characteristics because they have to provide instant changes for objective function and boundaries. Thus, heuristic algorithms can answer to all conditions and problems
- Heuristic algorithms should be capable of re-generating acceptable high quality solutions, in other words robust, which are not dependent on the initial solution swarm. In this way, they can tolerate incorrect initial data or swarm.
- It should be easier to analyze the applied heuristic algorithm due to its flexibility and obtained solution quality compared with complicated algorithms which may not be eligible for considering their mentioned attributes.

- Various algorithm users expect more attractive interface or easier usage from algorithm designers. A useful algorithm should be capable of providing some visual tools such as graphics, figures which make algorithms more understandable. This fact is very important to support the interaction between machines/computers and users.

Heuristic algorithms are based on greedy *neighbourhood search* methods to improve initial solutions (swarm) step by step to reach the global optimum or approximate it [29]. Some heuristic-neighbourhood (local) search algorithms generate the local optimum based on initial solutions and this situation is common for iterative improvable algorithms. In some cases, the local optima could be far from the global optima and cannot approximate them. Besides, in the most discrete optimisation problems, necessary information may not be available to determine the useful initial solution heap. In order to eliminate some disadvantages of heuristic-local search methods, some options are aligned and providing clearness and generality;

- The heuristic-local search could be started with multiple initial solutions and apply the same number of iterations for them; however, randomly distributed different solutions may have high cost and this technique does not guarantee optimum solutions because of possible different aims of initial solutions.
- If researchers focus on defining a complex neighbourhood function rather than multiple initial solutions, they can probably obtain better solutions regenerated from previous ones.
- Researchers can use complex learning strategies to get information about running algorithms and then this information can be used to define the penalized solutions or districts in the feasible area. In this way, they can avoid processing the same solution repeatedly.
- It is acceptable that, if a movement from a solution to another takes the algorithm out from local optima and avoids falling hill climbing, this movement should be applied even if it is not beneficial because the primary purpose of local search methods is approximating the global optima as much as possible [12].

According to all information about advantages and disadvantages of heuristic algorithms with their insufficient aspects, researchers need to choose or improve methods and tools that should be flexible to tolerate various conditions.

In recent years, researchers have been trying to combine algorithms among these new tools with their knowledge elements to improve search quality and apply the hybrid algorithms' challenging problems. In this dissertation, we will also use the same way to obtain better solutions. Hybrid algorithms are able to give two advantages to researchers. Developed hybrid algorithms may

decrease the run time by developing calculation techniques or decreasing the number of iterations. On the other hand, the hybridization process can make an algorithm more robust and flexible. In this way, developed algorithm can tolerate more noise and/or missing data and changing conditions [11].

In recent years, most optimisation problem researchers are trying to develop new algorithms and apply them in case studies and real world optimisation problems. Kovacevic et al. [13] developed a new meta-heuristic method and applied it to determine optimal values of machining parameters traditionally performed by algorithms based on mathematical models and exhaustive iterative search. The main reason for the meta-heuristic model in [13] is that, meta-heuristic methods are capable of handling various optimisation problems and obtaining high quality solutions by running less iteration, in other words less computational time. Their motivation for the development of the software prototype was obtaining sufficient solutions from the meta-heuristic algorithm. Li et al. [14] applied a particle swarm optimisation approach -a branch of heuristics- and developed an adjustment strategy for weighted circle packing problems which is a kind of important combination optimisation problem and has an NP-hard characteristic. The purpose of this [14] study is to obtain a better layout scheme for larger circles and show that the proposed method is superior to the existing algorithms in performance. Liu and Xing [15] constructed a special heuristic method for the double layer optimisation problem proposed to answer rapid developing logistic systems via advanced information technologies by reforming the current system. In [15], experimental results correctly proposed methods and heuristic feasibility. Kaveh and Khyatazadat [16] developed a new branch of heuristic methods called ray optimisation. The main idea of this new optimisation method is based on Snell's law about light travel and its refraction— in other words its direction changes. The purpose of this [16] development is to increase the effectiveness of optimisation elements in search phase and converge phase. Min et al. [17] searched for efficient algorithms to find the best orientation between two randomly deployed antennas -capable of determining the best orientation to receive the strongest wireless signal- under the effect of various wireless interferences. In [17], four different heuristic optimisation methods with some modification are presented as candidates and are also described with test cases and real world experiments to determine which algorithm is suitable to apply.

On the other hand, heuristic algorithms involve a few disadvantages beside their advantages. Firstly, heuristic methods usually take longer convergence time in comparison with deterministic methods. In case we consider mathematical based problems, deterministic methods such as Quasi-Newton method, golden section search, and quadratic fit search would be more useful due to shorter convergence time than heuristic methods spend. Besides, deterministic methods are able to reach

exact solutions for deterministic problems. However, if heuristic algorithms are applied on deterministic methods, they may not reach exact solutions.

In this study, one heuristic method is tackled and modified with another one to obtain a better solution for a specific NP-hard real world problem. Before implementation of these algorithms, braches of heuristic optimisations are described briefly.

2.3.1 Evolutionary Computation

In the last decades, many researchers have been interested in evolutionary based algorithms and the number of studies about this field has increased significantly and all these studies are considered subfields of evolutionary computation [18]. This algorithm simulates the hypothetical population based natural evolution optimisation process on a computer resulting in stochastic optimisation methods. This way can obtain better solutions than traditional methods in difficult real world optimisation problems [11].

Evolutionary computation mainly consists of evolutionary programming, evolution strategies, genetic algorithms, and differential evolution. Besides, many hybrid algorithms replicate some evolutionary algorithm attributes. Generally, all these algorithms require five major elements; genetic representation of solutions, generator methods for initial solutions population, fitness evaluation function, and operators differentiating the genetic structure and values of control parameters. Evolutionary algorithms improve all the solution population instead of one single solution [18]. In this way, these algorithms are able to increase their effectiveness and convergence speed while searching for global optimum/optima.

2.3.1.1 Genetic Algorithm

Genetic algorithm is based on generating a new set of solution populations from the current one inspired by the conjecture of natural selection and genetics to improve the fitness of solutions. This process continues until the stopping criteria are satisfied or the number of iterations reaches its limitation. Genetic algorithms involve three elements to obtain sufficient results from a search: reproduction, crossover, and mutation [19].

The reproduction operator works with the elimination of candidate solutions according to their quality inspired by natural selection. The crossover operator provides generating hybrid structures

to increase the number of outputs. The mutation operator is a basic structure of a genetic algorithm inspired by natural genetic mutation by checking all bits of solutions and reversing them according to their mutation rate. These operators generate more candidate solutions to increase the number of options [18].

Genetic algorithm is different from other search methods due to its specialized attributes: multipath search to reduce the possibility of being trapped in local optimum area, coding parameters themselves to make genetic operators more efficient by minimizing step computation, evaluating only objective function (in other words, fitness) to guide the search, no requirement for computation of derivatives or other auxiliary functions to make this algorithm easy to apply, and searching space with high probability of obtaining improved solutions [11]. These attributes make the genetic algorithm applicable to all kinds of problems such as discrete, continuous, and non-differentiable problems [19].

Genetic algorithm can be applied to bin packing problems. Goncalves and Resende [20] developed a kind of genetic algorithm named novel biased random key (BRKGA) for 2-D and 3-D bin packing problems, which can be more complex than 1-D bin packing problems according to their shape complexity. They improved the solution quality significantly with a modification on the placement algorithm. In this way, they proved that an applied placement algorithm can outperform all other ones.

2.3.1.2 Evolution Strategies and Evolutionary Programming

Evolution strategies rely on the mutation process as a search operator and evolving the strings from a population size of one. Evolution strategies are similar to the genetic algorithm in a few aspects. The major similarity between them is using selection process to obtain the best individuals from potential solutions. On the other hand, three main differences between genetic algorithm and evolution strategies can be expressed as: type of operated structures, basic operators they rely on and the link between an individual and its offspring they maintain [11].

Evolutionary programming (EP) is a stochastic optimisation method developed by Lawrence J, Fogel and his co-workers in the 1960s. Evolutionary programming has also many similarities with the genetic algorithm like evolution strategies. However, this technique does not imitate nature like the genetic algorithm emulates a specific genetic operator; EP emphasizes the behavioural link between individuals and their off-spring like evolutionary strategies do. In this way, EP does not involve mutation or crossover operations together [21]. In fact, evolutionary programming and evolutionary strategies are similar but developed by applying different approaches [11]. Evolutionary

programming was thought as an applicable method just for evolving finite states for prediction tasks for a long time. After a while, it appeared that this method is also eligible to optimise the continuous function with real valued vector representation [21].

2.3.1.3 Differential Evolution

Differential evolution is the most powerful population based optimisation method with its simplicity [22]. Mutation operation is also processed by the DE algorithm like other sophisticated evolutionary algorithms. However, the main difference between them is the type of applied method for the mutation process. The method the DE algorithm applies is using differences of random pairs of objective vectors [11]. Random candidates (pairs) are generated by different techniques and if new generated candidates beat existing ones, new pairs replace them and in this way, the DE algorithm acquires a more efficient search technique to find the global optimum [22].

The differential evolution algorithm is a direct search method based on a stochastic process and is considered as accurate, reasonably fast and robust. It is easy to apply for minimization processes in real world problems and multimodal objective functions. Mutation operation process in the DE algorithm uses arithmetical combinations of individuals whereas the genetic algorithm uses the method of perturbing genes in individuals with small probability. Besides, DE algorithms do not use binary representation unlike genetic algorithms for searching. Their search works with floating point representation. All these main characteristics make this algorithm a competitive alternative and attractive especially for engineering optimisers [11].

2.3.2 Swarm Intelligence

Researchers have recently been interested in swarm intelligence by imitating animals' foraging or path searching behaviours like in *Particle Swarm Optimisation, Ant Colony Optimisation* and *Bee Colony Optimisation.*

2.3.2.1 Particle Swarm Optimisation

Particle swarm optimisation (PSO) is based on simulating a swarm of birds foraging, initially introduced by Kennedy and Eberhart in 1995 [23]. The PSO algorithm is initialized with random solutions (swarm) like other sophisticated evolutionary computation algorithms [11]. Swarm and particles correspond to the population and individuals in other evolutionary computation techniques

respectively. Particles of a swarm move in multi dimensional space and each particle's position in this space is adjusted according to their and their neighbours' performance [24].

The PSO algorithm is similar to other population based algorithms in many aspects. PSO is also useful for optimising a variety of difficult problems. Besides, it is possible that the PSO algorithm can show higher convergence performance on some problems. The PSO algorithm requires a few parameters to adjust and this attribute makes the algorithm more compatible with implementations. On the other hand, PSO can fall into local minima easily [24].

Liu et al [20] improved on a formulation for 2-D bin packing problems with multiple constraints abbreviated as (MOBPP-2D). They proposed and applied a multiobjective evolutionary particle swarm optimisation algorithm (MOEPSO) to solve MOBBP-2D and performed the formulation with MOEPSO on various examples to make a comparison between the developed formulation embedded particle swarm algorithm and other optimisation methods introduced in the paper. This comparison illustrates the effectiveness and efficiency of MOEPSO in solving multiobjective bin packing problems.

2.3.2.2 Ant Colony Search Algorithm

Basically, an ant colony optimisation algorithm (ACO) imitates the foraging activities of an ant colony based on a random stochastic population. The ACO algorithm is a considerable method for optimising combinatorial optimisation problems and real world applications. Ant colonies have an interesting behaviour in that they can find the shortest path to reach a food source from their nest while foraging. In order to find or change the path the colony uses, each ant deposits on the ground a chemical substance called a pheromone. Marked paths by strong pheromone concentration allow ants to choose their path to find the nest or food sources in quasi random fashion with probability. Basically, the ACO algorithm applies two procedures: specifying the way of solution construction performed by ants for the problems and updating the pheromone trail [25].

Fuellerer et al [26] considered a 2-D vehicle loading as part of the routing problem. Probable solutions to this problem involving routing success depend on loading success and should satisfy the demand of the customers. They applied different heuristic methods to obtain an optimum solution for loading part and applied ant colony algorithm (ACO) for overall optimisation. Determinative factors of this problem are size of the items and their rotation frequency. Gathering information about these factors allow us to make low cost decisions in the transportation sector. Fuellerer et al's investigation about the combination of different heuristic methods with ACO was insufficient; however, in [26] their approach obtained sufficient results for this combination.

2.3.2.3 Artificial Bee Colony (ABC) Algorithm

The bee colony algorithm is one of the most recent population based metaheuristic search algorithms first systematically developed by Karaboga [29] and Pham et al [30] in 2005. Independently however these two are slightly different. Basically, they use the same techniques to generate initial swarm explained in the next chapters; however, they use different elimination technique for bees.

As mentioned in previous sections, scientists are inspired by natural occurrences and they investigate the behaviours of creatures to adapt these behaviours to the artificial systems. The main reason for simulating nature rather than applying mathematical calculations is that, creatures can overcome the problems they face every moment with guidance of their instincts. In this section, a bee swarm behaviour based algorithm is introduced step by step.

Basically, the Artificial Bee Colony (ABC) algorithm applies two main search methods as a combination, neighbourhood search and random search, to obtain optimum solutions for various problems. The ABC algorithm is inspired by food searching techniques and shares information about sources between bees in a honey bee swarm. Moreover, the ABC algorithm includes a hierarchical system and in this way, the bee swarm assigns bees and divides them according to their mission in the swarm. Definitions for bees' missions can change throughout the food search. Even though the ABC algorithm is a recently developed algorithm, it is considered very promising by many researchers with sufficient results from experiments in a variety of optimisation problems. The ABC algorithm is also eligible for modification or as part of a combination with other algorithms as the main characteristic of heuristics. There are many studies about the ABC algorithm.

Karaboga inventor of the ABC algorithm has also published papers about this algorithm and improved his idea over time. Karaboga and Ozturk [31] applied the ABC algorithm for data clustering, used in many disciplines and applications as an important tool for identifying objects based on the values of their attributes, on benchmark problems and compared with the Particle Swarm Optimisation (PSO) algorithm and nine other classification techniques [31]. On average, the ABC algorithm achieved better optimum solutions as a cluster than other algorithms for a variety of tackled datasets in [31]. Akay and Karaboga [32] applied a modified ABC algorithm for real parameter optimisation to increase the efficiency of the algorithm and the results of this modified algorithm and three other algorithms were compared. In [32], the standard ABC algorithm and modified ABC algorithm present different characteristics with different kinds of problems. In this study, ABC algorithm techniques developed by Karaboga are applied on the problem we tackle as a

base because ABC algorithm involves a swarm based search which is based on starting to search from multiple points in feasible area which means that ABC algorithm is capable of reducing convergence (to global optimum) time. Besides, studies about ABC algorithm [30], [31], [32] express the other valuable aspects of this algorithm and all these factors lead us to focus on this algorithm.

Pham et al [30] developed the bees algorithm as mentioned above and they demonstrated the efficiency of the newly developed algorithm on different functions. The results of the bees algorithm are sufficient and very promising for further studies. There is another study that shows the efficiency of the bees algorithm by applying it on a real world problem, also published by D.T. Pham as a participant in [33]. Xu et al [33] applied a binary bees algorithm (BBA), which is different from a standard bees algorithm, to solve a multiobjective multiconstraint combinatorial optimisation problem. They demonstrated the treatment of this algorithm by explaining the change of parameters.

Many other researchers have also benefited from the bees algorithm. Dereli and Das [34] improved a hybrid bees algorithm for solving container loading problems. The aim in this problem is loading a set of boxes into containers which are discrete variables to be worked. They explain the necessity of applying a hybridized algorithm for the container loading problem and comparing the mentioned hybrid algorithm with other algorithms known in literature. The study demonstrates that, according to the results, the hybridized bees algorithm obtains promising solutions and the standard bees algorithm is also very stimulating with its techniques for further studies in optimisation. Kang et al [35] also proposed a hybridized algorithm for searching for numerical global optimum and this algorithm was applied on a comprehensive set of benchmark functions. In [35], the results show that a new improved algorithm is reliable in most cases and is strongly competitive. Ozbakir et al [36], developed the standard bees algorithm (BA) to apply a generalized assignment problem, which is an NP-hard problem, and compared this algorithm with several algorithms from the literature. In order to investigate the performance of the proposed algorithm further, they applied it on a complex integer optimisation problem. According to the results and comparisons between several algorithms, they found the bees algorithm and proposed algorithm promising and these algorithms can be improved further. Gao and Liu [37] also improved the standard artificial bee colony (ABC) algorithm by using a new parameter with two improved solution search equations and then applied the new algorithm on benchmark functions and compared it with different algorithms according to their convergence performance for numerical global optimum. The results of the improved ABC algorithm show sufficient performance in all criteria. They also strongly recommend other researchers to carry out further studies about the bees colony algorithm. Xiang and An [38] improved the standard

artificial bee colony to accelerate the convergence speed. Besides, they made a change in the scout bee phase to avoid being trapped in local minima. In [38], several benchmark functions are tested by applying the improved algorithm and two other ABC based algorithms for a comparison between the mentioned algorithms. According to test results, the improved algorithm can be considered as a very efficient and robust optimisation algorithm. Szeto et al [39] proposed an enhanced version of the standard ABC algorithm to improve the solution quality. They applied the standard and enhanced ABC algorithm for one of the real world problems, which is the capacitated vehicle routing problem by using two sets of standard benchmark instances. In comparison, the enhanced algorithm outperformed the standard algorithm.

All these papers about the bees colony or artificial bee colony algorithm show that there is a wide area for possible and promising improvements for the standard ABC algorithm which is also eligible for modification by using different equations, formulations or parameters. It is also possible that other heuristic/deterministic algorithms with entire structure or a minor part can be merged with the ABC algorithm easily. The main objective of improvements or hybridizations on the ABC algorithm is obtaining better solutions and making the algorithm more robust. There are not only advantages to the ABC algorithm, it has also some disadvantages. Even though convergence speed of the ABC algorithm can be sufficient in most studies, the robustness of the ABC algorithm needs to be improved because a robust algorithm is not affected by parameter changes or misleading starting points and it can obtain approximately same results in this circumstance.

All creatures use different techniques for foraging repeatedly in a sequence with guidance of their instinct. The ABC algorithm mimics the bee behaviours in swarm and nature as mentioned above and uses the same collective intelligence of the forager honey bee. There are three main components of the ABC algorithm: food sources, employed foragers and unemployed foragers. Besides, forager bees use two main behaviours, recruitment for a nectar source and abandonment of a nectar source [29].

Food Sources: The source eligible or not for foraging visited by honey bees can be chosen due to its overall quality. There are many factors to measure the food source quality such as the distance between nest and source, food level, and nectar quality [29]. In the ABC algorithm, every single food source represents a possible solution in a feasible area and the overall food quality represents the fitness of possible solutions as well [40].

Employed Foragers: Forager bees are sent to food sources explored and determined by scout bees to exploit the nectar until they reach their capacity. Forager bees are not only carrying the nectar,

they also transfer information about food sources to share with other unemployed bees. The information about food sources is shared with certain probability. In this way, scout bees can determine the best food source in the environment they investigate and onlooker bees can find the food source easily.

Unemployed Foragers: Unemployed bees consist of two types, onlooker bees and scout bees. Scout bees search the environment surrounding the nest for new sources or update information about existing sources. Onlooker bees wait in the nest to gather information about food sources from employed bees or scout bees. In a hive, the percentage of scout bees is between 5-10% [29].

Collective intelligence of bee swarms is based on the information exchange between honey bees. Every single bee shares the information they have on a kind of stage with others. In this way, they can do their job with minimal failure. The most important occurrence while they exchange information is a kind of dancing on a stage in the hive. This dance is called a *waggle dance*.

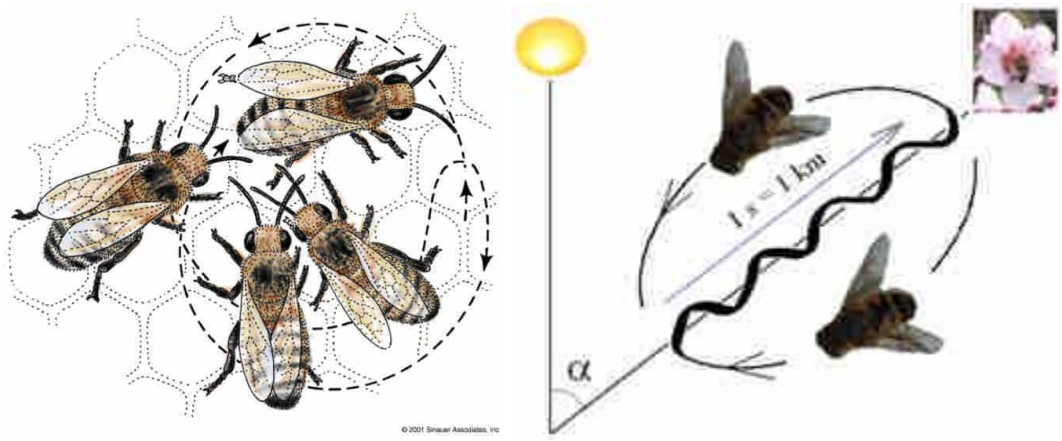


Fig. 3: The Waggle Dance Performed by Honey Bees [58]

Austrian ethologist Karl von Frisch was one of the first people to translate the meaning of the waggle dance. If the food source is less than 50 metres away from the hive, the bee performs a round dance otherwise it performs a waggle dance. In addition, honey bees perform a waggle dance with different movements and speed. In this way, they can communicate among the swarm and share information about food sources.

The waggle dance consists of five components [41]:

- Dance tempo (slower or faster)

- The duration of the dance (longer duration for better food source)
- Angle between vertical and waggle run means angle between sun and food source
- Short stop in which the dancer shares the sample of food source with their audience
- Other bees follow the dancer (audience) to gather information from the dancer.

The audience of the waggle dance determines the most profitable food source according to dance figures and then they divide the food source environment. There is a foraging cycle in the collective intelligence. This cycle involves four types of characteristics to provide the necessary information to other bees:

- Positive Feedback: If the highest nectar amount of the food sources in an environment increases, the number of visitors (onlooker bees) increases as well.
- Negative Feedback: If the nectar amount of a food source is exploited completely or has poor quality, it is not found sufficient and onlooker bees stop to visit this source.
- Fluctuation: Random search process for exploring the promising food sources is carried out by scout bees
- Multiple interactions: As mentioned above, scout bees and forager bees share their information about food sources with onlooker bees on the dance area [29].

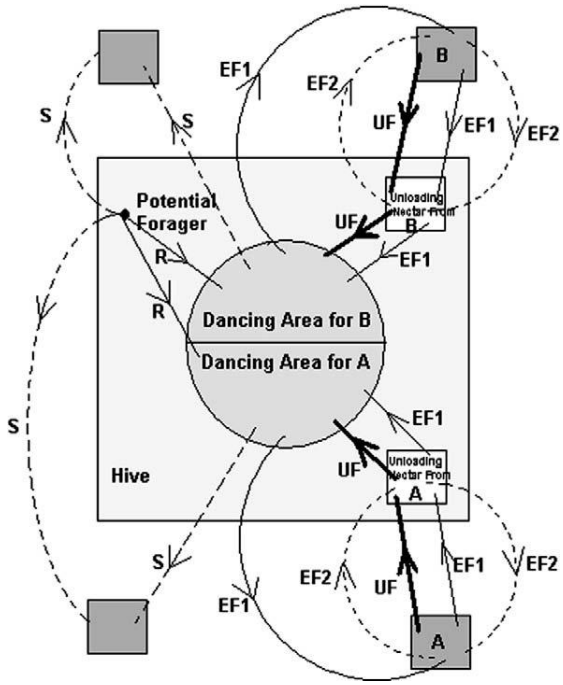


Fig. 4: The behaviour of honey bee foraging for nectar [29]

Abbreviations in Fig. 4 represent the following: Scout bees (S), newly recruited (onlooker) bees (R), uncommitted follower bees after abandoning the food source (UF), returning forager bees after

performing a waggle dance for an audience (EF1), and returning forager bees without performing a waggle dance (EF2) [40].

2.3.2.3.1 Formulation of ABC Algorithm

In the ABC algorithm, the number of onlooker bees or employed bees equals the number of solutions in the populations. In fact, there is no difference between onlooker bees or employed bees in the ABC algorithm because the initial population cannot be changed; however, in nature it can be changed due to the needs of the swarm.

As the first step, the initial population is generated randomly for solutions in a feasible area. In the ABC algorithm, initial solutions represent the food source positions in an environment. Each solution x_i (i = 1, 2, … SN) is a K-dimensional vector where K is the number of characteristics, in other words the parameters of the investigated solution in optimisation, and SN is the size of the initial population. Parameters for each solution can be represented as k (k = 1, 2, …, n) and the following definition might be used for initialization to generate the solution vector:

$$x_{ik} = l_k + rand(0,1) * (u_k - l_k) \quad (2)$$

where; l_k and u_k are the lower bound and upper bound of the parameter x_{ik} , respectively. After generating the initial population with their parameters, bees can separate and start the second phase. It is important that after generation of food sources, every single bee goes to only one food source in the employed bees phase.

In the employed bees phase, all bee swarms separate to the source field homogeneously and every single food source represents one honey bee. The employed bees search for new possible food sources (v_i) and this process is a kind of random neighbourhood search; so, they move from the memorized source (x_i) to the neighbour source to investigate the food quality and food level. Neighbour solutions around the initial solutions in a cycle have different fitness value and the honey bees evaluate them in this phase. The following equation defines the neighbourhood function to generate the neighbour solutions;

$$v_{ik} = x_{ik} + \phi_{ik} (x_{ik} - x_{mk}) \quad (3)$$

Where x_m is randomly selected food sources, i is a randomly chosen parameter index and ϕ_{ik} is a random number positive or negative in range. After generating the neighbour food sources, the bees evaluate the sources and they make a greedy selection according to fitness values of neighbour food sources. The fitness value of the solution $fit_i(x_i)$, can be calculated with the following equation;

$$\mathrm{fit_i}(\mathrm{x_i}) = \begin{cases} \frac{1}{1+\mathrm{f_i}(\mathrm{x_i})} & \text{if } \mathrm{f_i}(\mathrm{x_i}) \geq 0 \\ 1 + \mathrm{abs}\big(\mathrm{f_i}(\mathrm{x_i})\big) & \text{if } \mathrm{f_i}(\mathrm{x_i}) < 0 \end{cases} \quad (4)$$

Where $\mathrm{f_i}(\mathrm{x_i})$ is the objective function value of solution $\mathrm{x_i}$.

After greedy selection between memorized food source and neighbour food sources, employed bees determine the best one in this neighbourhood. As a result of greedy selection, if there is a better valued food source than a memorized one, the bees memorize the new one and forget the existing food source and then they transfer this information to the hive as feedback.

In the onlooker bee phase, employed bees and onlooker bees as a subgroup of unemployed bees meet on the dancing area and employed bees share the information by performing a waggle dance to communicate to other bees. While employed bees perform the waggle dance, onlooker bees evaluate the dance figures and determine the food source. In the ABC algorithm, the food source selection according to their fitness value by onlooker bees can be formulated as in equation (5). The probability value $\mathrm{p_i}$with $\mathrm{x_i}$ can be calculated by using this expression. In order to select food sources according to their $\mathrm{p_i}$ value, a special technique can be used in the ABC algorithm such as the roulette wheel selection method [29].

$$p_i = \frac{fit_i(x_i)}{\sum_{i=1}^{SN} fit_i(x_i)}. \quad (5)$$

The roulette wheel selection method works by calculating the cumulative sum of all fitness values. After this calculation, random numbers which correspond to the range of the fitness of a solution in cumulative sum are generated and the bee is assigned to the food source position according to these random values.

Scout bees which are the other type of unemployed bees, search for food sources randomly. If an employed bee cannot find better food sources around the predetermined one after several neighbourhood greedy searches, they abandon that area and inform scout bees about it. Scouts search for a new food source randomly and inform onlooker bees about the position of the source. In other words, in the ABC algorithm, if a solution cannot be improved for predetermined times, called the search limit, it is erased from memory and another solution is re-generated randomly instead of the abandoned one and memorized. In this study, erasing the information about the abandoned solution is investigated [40].

The ABC algorithm can be explained briefly as in Fig. 5;

In addition, an ABC algorithm flowchart is demonstrated in Fig. 6. The ABC algorithm has some disadvantages beside its advantages. For instance, many researchers have proposed several models to enhance the ABC algorithm because of its weak robustness (explained in page 30) characteristic especially. In this study, we will try to overcome weak robustness characteristic of ABC algorithm with some additional techniques explained in the next chapter.

```
1: Initialize the population of solutions xi,  (i = 1, …, SN)
2: Evaluate the population
3: cycle = 1
4: repeat
5:     Produce new solutions vi for the employed bees from existing solutions by
       using (3) and evaluate them
6:     Apply the greedy selection process for the employed bees
7:     Reset the counter if solution is improved otherwise add one to counter
8:     Calculate the probability values Pi for the solution xi by (5)
9:     Produce an amount of new solutions vi for the onlooker bees from the
       solutions xi depending on Pi and evaluate them
10:    Apply the greedy selection process for the onlooker bees
11:    Reset the counter if solution is improved otherwise add one to counter
12:    Check the counter for solutions if they exceed the limit or not and
       determine the abandoned solution for the scout, if exists, and replace it
       with a new randomly produced solution xi by formulation (2)
13:    Memorize the best solution achieved in one cycle
14:    cycle = cycle + 1
15:    until predetermined number of cycle [40].
```

Fig. 5: Pseudo Code for Classic ABC Algorithm

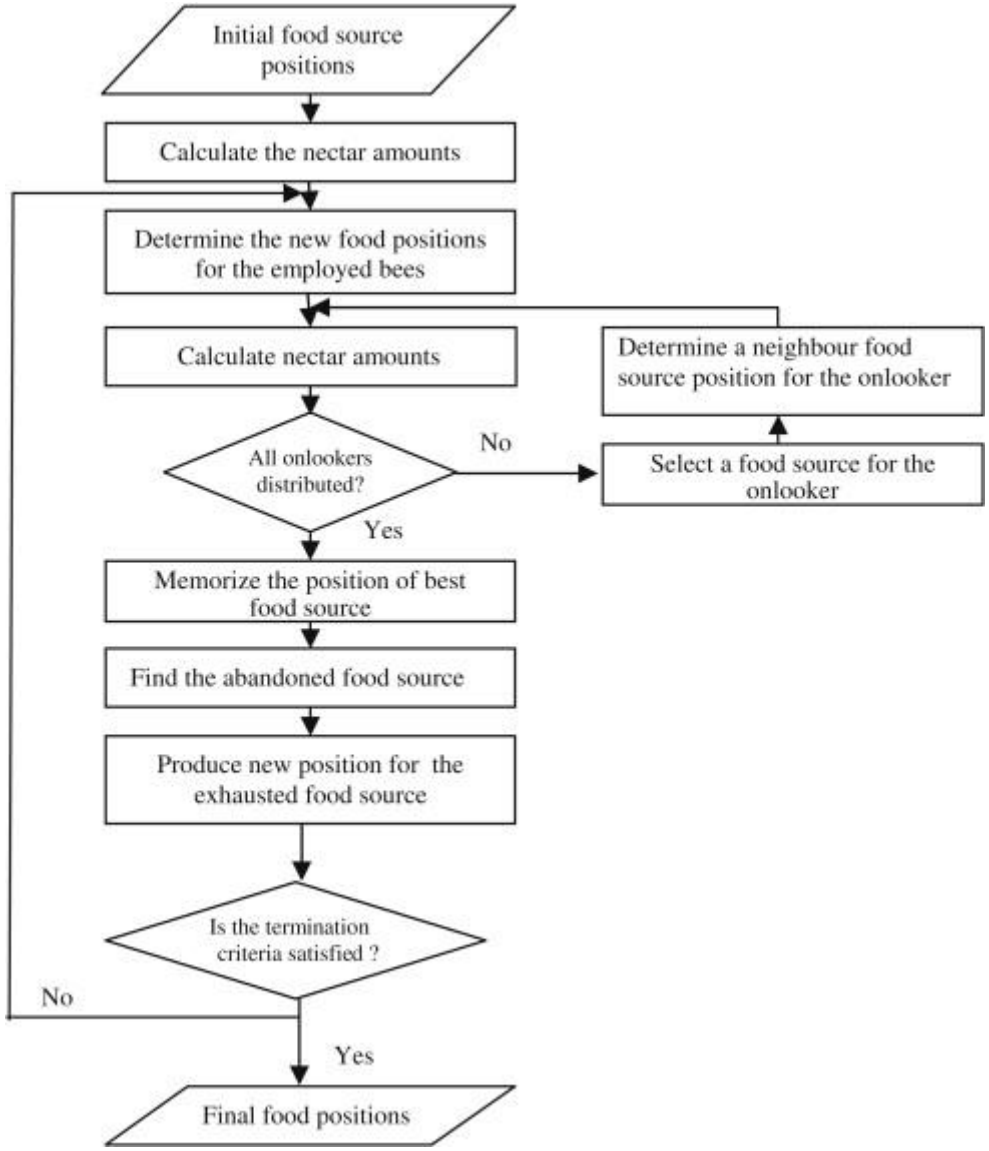


Fig. 6: Artificial Bee Colony (ABC) Algorithm Flowchart [32]

2.3.3 Individual Solution Driven Heuristic Algorithms

2.3.3.1 Simulated Annealing

A simulated annealing technique is based on the metallurgical process of materials where if they are heated and then cooled slowly, the space between the crystal elements of the material tends to the global minimum by avoiding hill climbing in local minima. The heating and cooling process is controlled by a temperature parameter [27]. The simulated annealing algorithm is eligible for a large combinatorial optimisation problem involving an appropriate perturbation system, cost function, solution space, and cooling schedule. The effectiveness of the simulated annealing method can be observed easily in network reconfiguration problems by making a change to the system size. Besides,

the cost function is helpful for the simulated annealing algorithm to escape more easily from local minima and to perform rapid convergence [11].

Rao and Iyengar [28] proposed an efficient version of the simulated annealing method compared with well-known heuristic algorithms according to implementation results of a variant of the bin packing problem. They obtain sufficient and high quality solutions by applying the developed algorithm.

2.3.3.2 Tabu Search Method

Tabu search (TS) algorithm is metaheuristic and was developed by F. Glover. The purpose of the TS algorithm is to increase the performance of the neighbourhood search function applied on many heuristic algorithms by improving the search techniques. The TS algorithm provides a further search beyond the existing best solution in a feasible area by using the best move in the previous cycle to generate a new solution. In other words, the TS algorithm memorizes the best move in iteration [42].

As the TS algorithm proposes a more efficient neighbourhood search for general heuristic optimisation problems, many researchers use this method to enhance the algorithm applied on tackled problems. In other words, the TS algorithm is a promising method for further studies.

Mashinchi et al [43] proposed a new algorithm based on the Tabu Search and Nelder Mead (NM) search strategy with an additional phase for increasing the robustness of the proposed method. They applied the new developed algorithm on a real world problem which is global continuous optimisation problems. They applied the TS method to enlarge the search field and decrease the possibility of being trapped in local minima. In this way, convergence speed of the proposed hybrid algorithm can be accelerated and this speciality can make the mentioned algorithm competitive in comparison with other algorithms. The proposed algorithm has two main advantages; it is applicable for any global continuous optimisation problem without considering any constraints and it shows better performance for small and medium input domains in the given multimodal functions. Ji and Tang [44] proposed a new tabu search based on applying a memory system for solving the multiple minima problem of continuous functions. The proposed method is based on two convergence theorems introduced by them. Numerical results show that proposed algorithm is efficient, robust and suitable for implementations. Ahonen et al [45] applied the tabu search method on several corridor allocation problem instances with different datasets generated randomly or taken from literature to compare with the simulated annealing algorithm. The results show that the simulated annealing algorithm outperforms the tabu search method. This paper [45] shows that the

effectiveness of an algorithm depends on problem type and characteristics of datasets. The scheduling problems have been challenging in the last few decades and one of them is tackled by Belle et al [46] who applied a tabu search approach for it. The purpose of this [46] paper is minimizing the total travel time and the tardiness in the truck scheduling problem. Calculating the optimum solutions with a mixed integer programming solver, using a mathematical model, takes a lot of computation time. They improved the results calculated by integer programming and shortened the computation time by applying the tabu search approach and stated that the proposed method is promising for future studies. Jia et al [47] developed a new tabu search working with mutation and mixed local search operators to overcome the weaknesses of the standard tabu search. In comparison, the proposed tabu search is much more sufficient than other algorithms according to vehicle route problem implementation results because it is more applicable on whether the size of the problem is big or small and the convergence speed is fast with efficient calculation. Tao and Wang [48] proposed a new tabu search approach for the 3-D loading sub-problem of the vehicle routing problem (3L-CVRP), which combines the routing of a fleet of vehicles and the loading of 3-D shaped goods. The purpose of this [48] paper is minimizing the total travel distance with minimizing the wastage. According to experiment results, the proposed approach shows higher performance compared with other algorithms in terms of both solution quality and efficiency.

The main idea of the TS algorithm is using memory to check the search history. Throughout the search, some bad moves can be memorized in the short term and added to a limited list called a Short Term Tabu List (STTL). The purpose of the STTL is to avoid being trapped in local minima and it works with a first in first out system. Besides, if a good move is found in a cycle it is added to long term memory called a Long Term Tabu List (LTTL). LTTL shows that the field containing a memorized solution has been investigated before. These two lists keep the memorized moves for a predetermined number of cycles and then they are erased.

The TS algorithm is a tool for escaping the local minimum and overcoming the hill climbing; however, the next point can be worse than the current one in a local minimum. In this way, the TS algorithm is protected from being trapped in the local minimum [43].

The TS algorithm generates a finite number of neighbours around the current solution and can consider these neighbours for the next iterations. Period of a move in the tabu list is a basic control parameter in the TS algorithm. Secondary control parameter is the size of the tabu list which denotes the determined maximum number of moves, in other words capacity, in the tabu list. The tabu list logic uses the first in first out (FIFO) algorithm to enroll the move into the list or erase it. Chosen move from neighbourhood search is enrolled to the tabu list for a period and at the end of

this period the move is erased from the list. If the tabu list is full, the first added move is erased and the chosen move enrolled instead of it. The basic Tabu Search algorithm based on STTL is illustrated in Fig. 7.

Several heuristic algorithms explained above have been applied in the last few decades to overcome real world problems which are difficult to solve by applying classic methods. Even though these algorithms are based on trial and error logic, they obtain promising and competitive results in real world problems.

In the next section, one of the real world problems, found interesting by researchers in recent years, is defined and detailed.

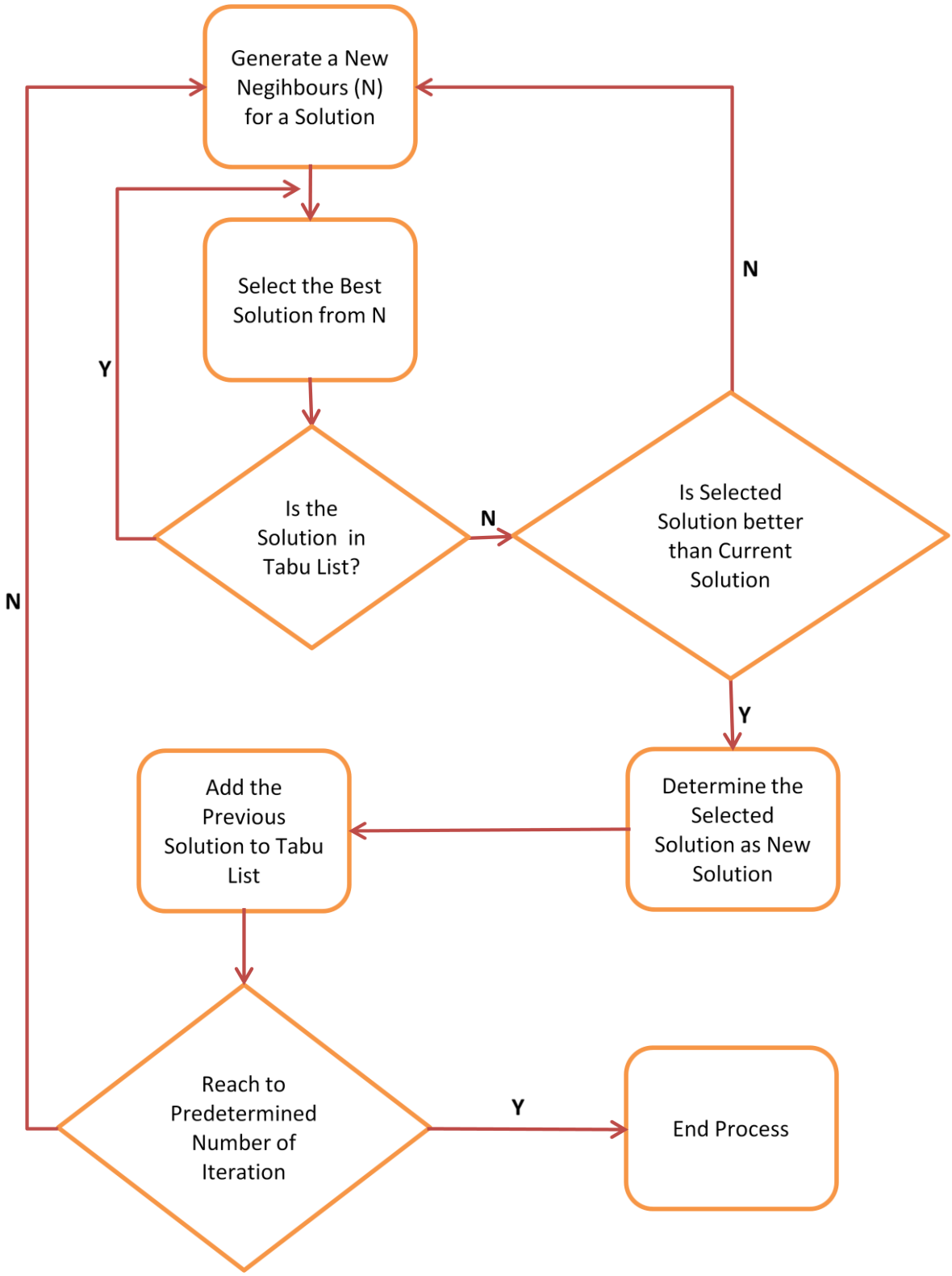


Fig. 7: Tabu Search Based on Short Term Tabu List

2.4 Bin Packing Problems

Engineers always have to overcome many real world problems and they may be unable to reach sufficient solutions to these problems in proper time. Because of this weakness of workers or engineers, scientific backgrounds provide them with suitable approaches for tackled problems. On the other hand, operators may also explore some approaches for their problems by using trial and error techniques. In both cases, they have to find an acceptable way to reach solutions.

One of these real world problems is called the Bin Packing Problem which involves basically loading a finite number of capacitated alike repositories with various dimensional shaped goods. The bin packing problem is a combinatorial NP-hard problem. Finding the optimum solution is known to be exponentially difficult. The object of bin packing problems is minimizing the number of bins and wastage.

Cutting stock problems are also a version of bin packing problems and the main objective is that, when the bin is stated as 1, this problem maximizes the number of packed items. Volume and value specialities are also determinative characteristics in cutting stock problems.

Many heuristic approaches have been developed and proposed including advantages and disadvantages to solve the bin packing problems. The bin packing problem can be categorized by dimensional characteristics and the problem definition is based on the relation between items and bins.

If all items and bins have two similar superficies, they can be categorized as a one dimensional (1D) bin packing problems set. If all of them have similar superficies, they can be categorized as a two dimensional (2D) bin packing problems set. If all items and bins have totally different superficies, they can be categorized as a three dimensional (3D) bin packing problems set.

Packing approaches may change due to the dimensional relation of bin packing problems sets. In this study, a set of the 1D bin packing problem is considered with classic algorithms and another heuristic approach.

Bin packing problem approaches involve the information about items' supply system. If the packing operator works with an offline supply system, the operator has all the information about items to allocate them into bins by categorizing due to their shape. On the other hand, if the packing operator works with an online supply system, the operator may not allocate the arrival items into bins as in the offline supply system. In this case, the supply system speciality is also determinative for bin packing problem approaches.

2.4.1 One Dimensional (1D) Bin Packing Problems

One dimensional bin packing (1DBP) problems can be considered as the easiest problem set in bin packing problems due to their simplicity. In the 1DBP, objects have a single dimension (cost, time, size, weight, or any number of other measures).

1DBP problems can be diversified such as stock cutting problem, weight annealing. by the agency of its dimensional simplicity characteristic used by many researchers for their studies. Berberler et al [49] considered a 1D cutting stock problem and proposed a new heuristic algorithm with a new dynamic programming operator to solve it. They compared the obtained results of the proposed algorithm with other 1D cutting stock problems to illustrate its efficiency. Loh et al [50] developed a new procedure using a concept of weight annealing to solve the 1DBP problem. They found the developed procedure applicable easily and applied it to a high number of instances. Obtained results show that, the proposed procedure generates high quality solutions in a significantly short time. Xavier and Miyazawa [51] presented hybrid approximation algorithms based on First Fit (Decreasing) and Best Fit (Decreasing) algorithms for a class constrained bin packing problem (CCSBP) in which items must be separated into non-null shelf divisions. The purpose of this [51] paper is to illustrate performance characteristics of First Fit, Best Fit, First Fit Decreasing and Best Fit Decreasing algorithms according to implementation results of proposed approximation.

In order to solve the Bin Packing (BP) problems, many heuristic methods are developed. Some of the most popular algorithms are described in the following discussions. In order to make clear the descriptions of the following heuristic algorithms, an example set of items is given so that the sequence is S= {4, 8, 5, 1, 7, 6, 1, 4, 2, 2} and the capacity of bins is 10.

- Next Fit (NF) Algorithm: "*Place the items in the order in which they arrive. Place the next item into the current bin if it fits. If it does not, close that bin and start a new bin* [56]." The result of using this algorithm is shown in Fig. 8. The result of the (NF) algorithm is six bins and this result is clearly wasteful; however, it is acceptable if the information about free space in previous bins is not available or accessible.

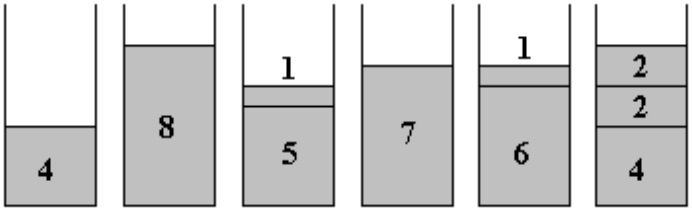


Fig. 8: Packing Under Next Fit Algorithm [56]

- First Fit (FF) Algorithm*: "Place the items in the order in which they arrive. Place the next item into the lowest numbered bin in which it fits. If it does not fit into any open bin, start a new bin* [56]*."* The result of using this algorithm is shown in Fig. 9. The result of the (FF) algorithm is five bins and this algorithm requires a memory of previous bins.

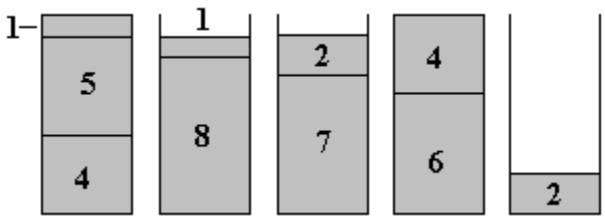


Fig. 9: Packing Under First Fit Algorithm [56]

- Best Fit (BF) Algorithm*: "Place the items in the order in which they arrive. Place the next item into that bin which will leave the least room left over after the item is placed in the bin. If it does not fit in any bin, start a new bin* [56]*."* The result of using this algorithm is shown in Fig. 10. The result of the (BF) algorithm is five bins as well and this algorithm also requires a memory of previous bins. The BF algorithm generally obtains the best solution in online algorithms.

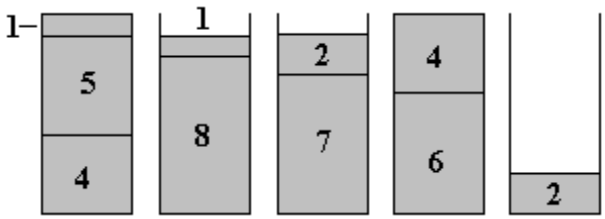


Fig. 10: Packing Under Best Fit Algorithm [56]

- Worst Fit (WF) Algorithm: "*Place the items in the order in which they arrive. Place the next item into that bin which will leave the most room left over after the item is placed in the bin. If it does not fit in any bin, start a new bin* [56]*."* The result of using this algorithm is shown in Fig. 11 and the result of the (WF) algorithm is five bins. This algorithm is useful if all bins are desired to be the same weight approximately, however it may not be useful for the upcoming items.

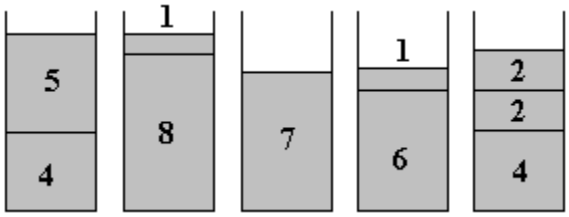


Fig. 11: Packing Under Worst Fit Algorithm [56]

- First Fit Decreasing and Best Fit Decreasing (FFD-BFD) Algorithm: "*Sort the items in decreasing order* [56]*."* In this case, the FF or BF algorithm can be applied because they obtain the same results. The result of using these algorithms is shown in Fig. 12 and the result of the (FFD-BFD) algorithm is four bins as the best result by the agency of working with the offline supply system, because the information about items are available altogether.

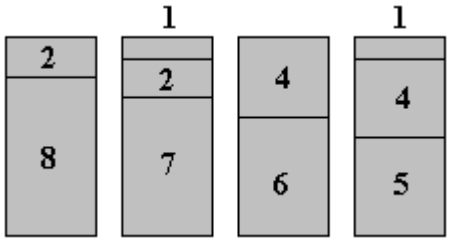


Fig. 12: Packing Under First-Best Fit Decreasing Algorithm [56]

In this study, 1D bin packing problem datasets are considered to be solved by another heuristic algorithm from literature.

2.4.2 Two and Three Dimensional (2D & 3D) Bin Packing Problems

2D and 3D bin packing problems could be more complicated than 1D bin packing problems because of loading complexity of items and bins. One of the main difficulties of the multi (2D-3D) dimensional packing problem is that, unusable spaces may not be rearranged as well as the waste in 1D bin packing problems [52]. Many heuristic approaches for multi dimensional bin packing problems are developed to solve the aforementioned complexities.

Aydin and Taylan [53] introduced a kind of scheduling problem model with the integer programming approach for optimisation. Tackled problem is a cutting process for large paper rolls in which pieces of paper can be cut in a horizontal or vertical order in a paper roll the same as the process in 2D strip packing problems. Epstein and Levy [53] studied multi dimensional bin packing problems and

specifically considered the 3D one. Besides, they developed an algorithm for the offline bin packing problem and also presented a dynamic version. Hifi et al [54] considered 3D bin packing problems and introduced a mixed integer linear programming formulation. The obtained results show the efficiency of the proposed method.

Many other studies about bin packing problems can be found in the literature in which there are several approximations, algorithms, formulations to obtain better solutions by a reduction in the number of bins, and several experiments for these approaches. In the next chapter, another approach for 1D bin packing problems is introduced.

Chapter 3: Proposed Approach

3.1 Fundamental Concepts of Proposed Approach

Bin packing problems is a kind of NP-hard knapsack problem and found interesting by many researchers. Several heuristic methods are proposed to solve the complexity of this real world problem. In this study, another heuristic method, the Artificial Bee Colony (ABC) algorithm is applied and enhanced with another heuristic method.

Several implementations of the ABC algorithm for bin packing problems can be found in the literature as in [34]. A general suggestion about the ABC algorithm is that it shows low quality robustness characteristic. It means that the ABC algorithm may not re-generate high quality solutions as well as other heuristic approaches. This weakness is investigated by many researchers as in [38] and other studies. The main reason for this weakness is the generating new solutions policy. Xiang and An [38] modified the generating process and proposed chaotic initialization instead of random initialization to avoid unpromising low quality solutions. It shows that the weakness of the ABC algorithm is based on generating low quality solutions and investigating them repeatedly. In this case, we have to focus on how to avoid undesired initial points in a feasible area.

One of several ways to avoid low quality solutions is saving the diversification of the population with reverse selection [38]. In this way, the solution with lower fitness value also can be selected to be improved because in some cases, solutions with larger fitness value may cause premature convergence and reverse selection can avoid this condition. Another way to avoid low quality solutions is embedding a memory in the ABC algorithm and to remember the low quality solutions by memorizing them.

It is a fact that, in the ABC algorithm, bees memorize only the solution with the best fitness value in a neighbourhood. As a result of greedy selection, bees forget the previous best solution. If they search for the same non-memorized low quality solutions repeatedly, this condition turns into hill climbing. If we prohibit the bee to visit the same solution in a period, it is obligated to visit other solutions in the same neighbourhood. In this case, we need a memory to mark the undesired solutions as prohibited moves.

The tabu search method provides the required memory with the Short Term Tabu List (STTL). As explained in the previous chapter, STTL saves the undesired moves for a predetermined period. The purpose of memorizing the low quality solutions is to escape from the local minimum by jumping to the solution from outside of the local minimum. In this way, we can search further for the global optimum.

Besides the advantages of escaping from the local minimum by the agency of the tabu list, there are also some risks in using a tabu search approach. It is a fact that, if we search in a global optimum curve, the tabu list may also prohibit the move leading the search to global optimum and even may take the search out of this promising curve.

It is another fact that, convergence speed may be fast and the search may reach the global optimum before none of the moves are prohibited and saved to the tabu list by the tabu search policy. Besides, the tabu period should be determined by the characteristics of the tackled problem.

3.2 Implementation of Proposed Approach

In the proposed approach, we need to generate a population at first like in other heuristic methods. Randomly distributed initial solutions involving wastage and number of used bins are generated to investigate for a global optimum search. In order to generate a random solution, the following items package method is used for loading the bins.

3.2.1 Problem Representation and Neighbourhood Structure

Traditional algorithms from literature for 1-D bin packing problems obtain fixed results; however, it does not mean that these solutions represent the exact solutions. There are possibly better solutions in the feasible area that cannot be found by the mentioned algorithms. In order to improve these fixed solutions and reach beyond them, we need to advance raw solutions by modifying item placement.

Every single modified solution is a neighbour of current solutions that could be better or worse in a comparison. New current solutions are generated by greedy search in all neighbourhoods and represent a new swarm.

3.2.2 Bin Loading Method

At first, the number of imaginary bins equals the number of items in the problem set in which the size of any item cannot exceed the bin capacity determined for loading. Items in the sequence are assigned to bins randomly until all items are put into them.

In Fig. 13 and the next few figures, a mini example item-set S = {5, 2, 3, 4, 7, 2, 3} with 10 capacitated bins is defined to explain the proposed loading method. In this example, seven items in a sequence are assigned to seven empty bins. If the assigned item does not fit the determined bin, another random number is generated for it until a suitable bin is found. As illustrated in Fig. 13, seven items were assigned to five bins and the last two bins are still empty. According to the first assignation, the raw result is five bins.

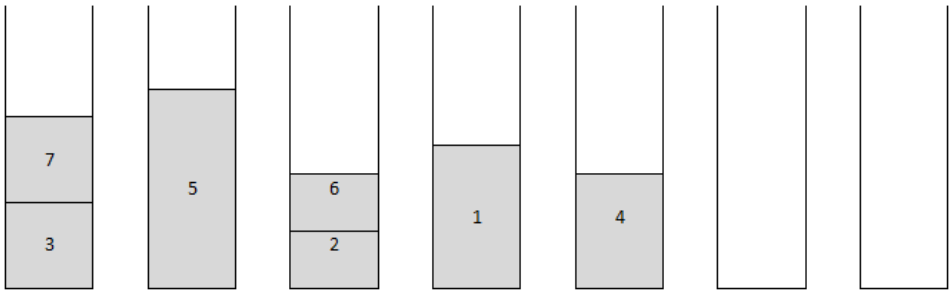


Fig. 13: Raw Assignation Result of Item-set Example in First Step

In the proposed loading method, the bins are combined again as a second step. If the combination of two or more bins does not exceed the bin capacity, they are counted as one bin with all inclusive items. It is important that any of the bins assigned in the first step is never divided to its items again for another combination because we assume all packed items in a bin as a single item.

As another rule in the proposed loading method, we assume that, if the percentage of packed items in a bin is equal or more than 50%, it is called a used bin and not combined with another bin. In this way, we ensure the randomness for solution diversification as much as possible.

The main reason for adjusting the usage level to 50% to be called a used bin is that, at least two bins can be combined if their usage levels are equal or less than 50%. If it is more than 50%, wastage of solutions could be high. On the other hand, the reason for disregarding the bin with usage level less than 50% is that, it is strongly possible that the upcoming items could fit this bin and it would be counted as a used bin after packaging one or more items in it.

The combination step starts with the first left non-empty bin in line having less than 50% in order to find a suitable bin through the line. As a result of this phase, there can be only one bin having less than 50% at most. According to these rules, the combined bins are demonstrated in Fig. 14.

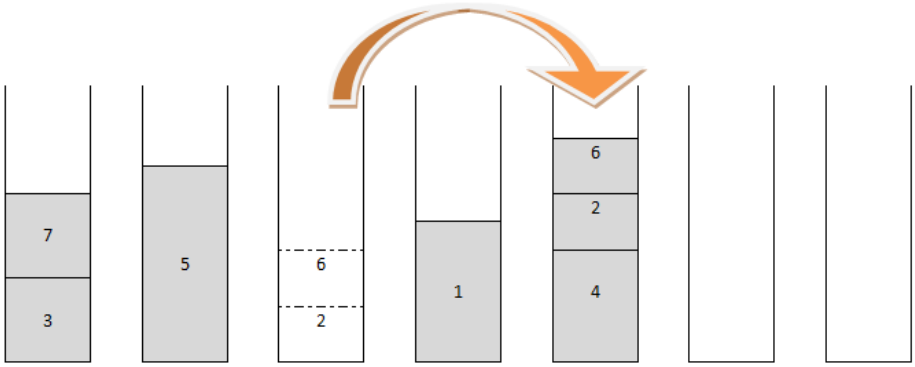


Fig. 14: The Result of Combination Process

Bin-3 and Bin-5 are less than 50% and after the combination process for bins, the modified result is four bins and the total wastage is 35% as shown in Fig. 15.

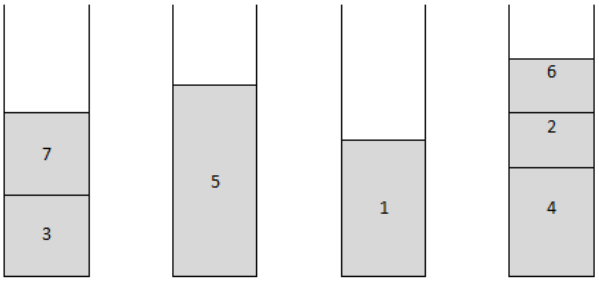


Fig. 15: Modified Result of Assignation for Items

All solutions in an initial population are generated by following aforementioned loading rules. After generating the initial population, neighbourhood function is defined as a tool for the next phase.

3.2.3 Generating a New Solution

In the second phase, all employed bees visit only one solution and generate a new solution from it by using the neighbourhood function as explained above. In the proposed approach, neighbourhood function to generate a new solution is explained as follows.

In order to generate a neighbour solution, an item not packed in a fully filled bin is chosen randomly and packed in another randomly chosen non-empty bin if it fits. In case there is not any suitable bin for the chosen item, it means that the solution cannot be diversified anymore. In Fig. 16, generating

a new solution is demonstrated. After generation, the result may not change for a number of iterations, however the diversified solution allows for further search.

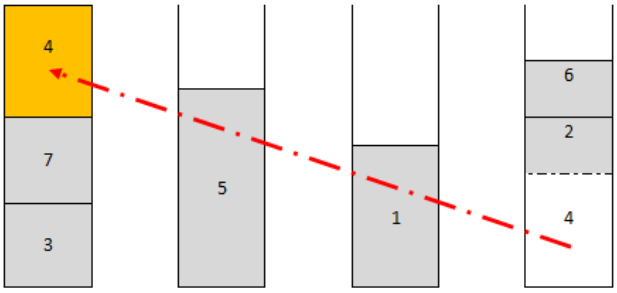


Fig. 16: Generating a New Solution

There may be some bins that are filled less than 50% after changing the chosen item's place like shown in Fig. 16. After moving the item to another bin, the original bin filling level decreased to less than 50%. In this case, the re-packaging rule in the proposed item is applied again as shown in Fig. 17.

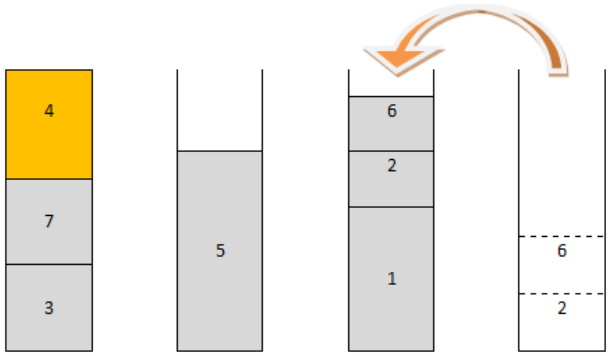


Fig. 17: Modification of Generated Solution

The result of generated solution changed by doing this modification as shown in Fig. 18 with three bins and 10% wastage. Generating a new solution is also used in onlooker bees phase in the same way. Proposed bin loading method can be modified with various approaches.

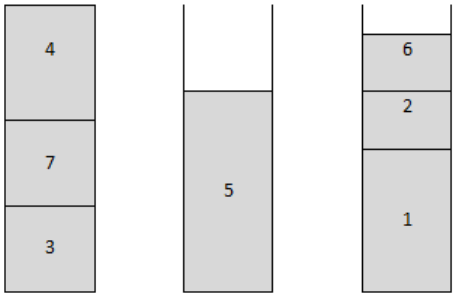


Fig. 18: The Modified New Solution

3.2.4 The Roulette Wheel Function

After generating a population for employed bees phase in the ABC algorithm, the roulette wheel function is used for assigning the onlooker bees to solutions randomly for neighbour search. This function may send two or more onlooker bees to the same solutions because of randomisation.

In the ABC algorithm, duties of onlooker bees are determined due to their probability value $\boldsymbol{p_i}$ calculated as in equation (5). According to this equation, the solution with high fitness value has a high chance for selection; however in bin packing problems, low fitness value for wastage is better to investigate. Because of the minimization purpose of bin packing problems, we need to change the equation of the roulette wheel function with another one as demonstrated in equation (6) to give a better chance of a solution with low fitness value.

$$p_i = \frac{1-fit_i(x_i)}{\sum_{i=1}^{SN} 1-fit_i(x_i)}. \quad (6)$$

After assignation of onlooker bees to the solution randomly, we apply a neighbourhood search function for selected solutions the same as in the employed bee phase and then apply greedy search to select the best fitness value among solutions.

3.2.5 Enhancement with Memory

As a result of greedy neighbourhood search, onlooker bees around the solution selected by roulette wheel function choose the best fitness value. If they have the information about a worse solution in their memory, they erase this information and memorize the best solution instead of it.

The ABC algorithm uses a counter to calculate the number of improvement failures. If employed or onlooker bees improve the solution, the counter for that solution is reset. Otherwise the counter is increased by one until the predetermined limit. If the counter exceeds this limit, the solution is

abandoned; however, it is important that the abandoned solution may be generated and visited repeatedly. This attribute signifies that the ABC algorithm does not memorize the history of neighbourhood search whether the abandoned solution is promising or not.

The main purpose of this study is providing the classic ABC algorithm with a memory to avoid repetition. In this way, the search in the ABC algorithm can escape from possible local optimums. The proposed ***"A Memory Embedded ABC Algorithm"*** works with ***Short Term Tabu List*** **(*STTL*)** described in the previous chapter.

According to the proposed algorithm, the abandoned solution is saved in STTL for a predetermined period. The length of the period depends on the characteristic of tackled item-set, so various lengths of periods should be tried to obtain better results. It is important that, in the proposed algorithm, bees do not memorize the move from the original solution to generated solution in greedy search. They do memorize only unimproved and abandoned solutions. By the agency of memory reinforcement, solutions that cannot be improved further are prohibited and bees are forced to visit different solutions for investigation. At the end of the tabu period of listed solutions, they are erased from the list and can be visited again in case search exigency.

Other operators of the proposed algorithm are the same as the traditional ABC algorithm. In the next section, the proposed algorithm is described by a computer software implementation.

3.2.6 A Software Implementation for Proposed Algorithm

In this study, MATLAB 2012 software is used for implementations. Item-sets are taken from a website referred to in the acknowledgement. Item-sets consist of two different distributions with two different bin capacities. We developed the proposed algorithm by keeping three steps.

Firstly, fundamental algorithms described in section 2.4 are implemented to obtain raw results to use as a reference point for comparison. Fig. 19.A demonstrates the window for implementation of the classic algorithm.

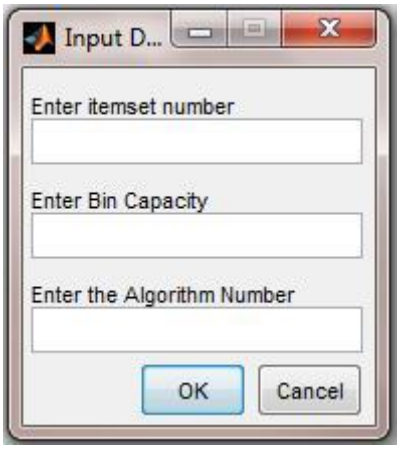


Fig. 19.A: Window for Traditional Algorithms

There are 20 sub item-sets for all item-sets grouped by their sizes. Besides, 5 fundamental algorithms can be implemented by typing the algorithm number in the relevant gap in the shown window.

The following step is the implementation of the traditional ABC algorithm and the final step is the implementation of the proposed memory embedded ABC algorithm. Fig. 19.B and 19.C show the windows.

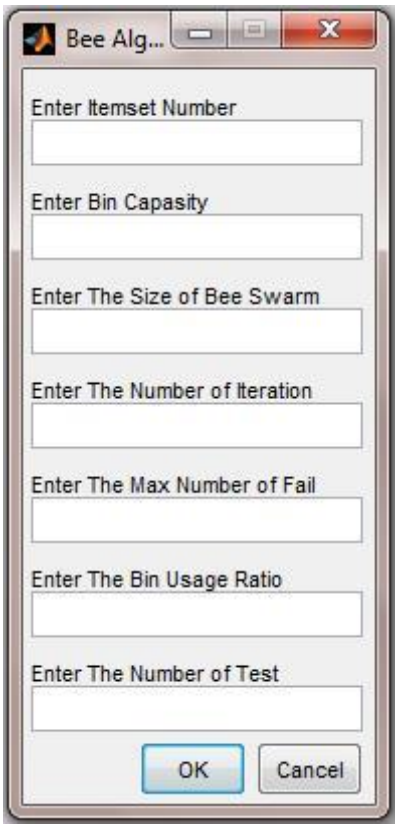


Fig. 19.B: Window for ABC Algorithm

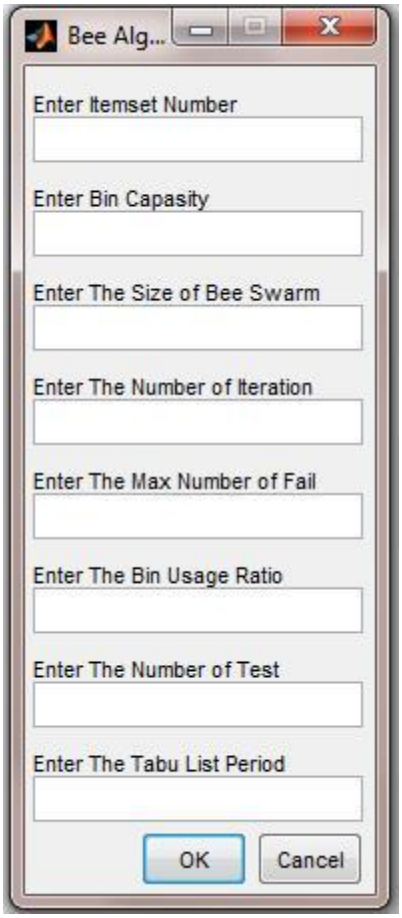


Fig. 19.C: Window for Proposed Algorithms

In the next chapter, experiment results obtained by the aforementioned software programmes are compared and discussed regarding their algorithm and item-set characteristics.

Chapter 4: Experimental Results and Discussion

In this chapter, a number of experiments are processed by applying methods which are explained in previous chapter. Before starting to experiments, we need to understand structures of applied datasets and then determine default parameter values to obtain sufficient results. After obtaining experimental results, relevant discussions are provided with overall discussion at the end of chapter.

4.1 Datasets

In this study, there are two classes of 1-D bin packing datasets acquired from [55]. The first 4 datasets consist of items of integer sizes uniformly distributed in (20, 100) to be packed into bins of size 150. The other 4 datasets consist of triplets of decimal sized items from (25, 50) to be packed into bins of size 100. For the triplets class, the optimum number of bins is equal to 1/3 of the number of items.

4.2 Parameter Settings

The main problem in experiments is to determine the default value for the software compilation process because before an experiment, results cannot be estimated if there is no reference experiment result. In this study, there are four main parameters: (i) size of bee swarm, (ii) number of iterations, (iii) number of failures allowance, and (iv) tabu list period for experiments. Different values were tried to find the best solutions.

The main criterion of value determination is the meaning of parameters for the applied algorithm. At first, swarm size should be sufficient for the search because the wider the swarm the more initial solutions. In case of wide swarm selection, researchers would be eligible for a deeper search in the feasible area. Besides, wider swarm improves the randomisation characteristic of the algorithm by decreasing the probability of bee placement for food sources in the onlooker phase in the ABC algorithm. For example, if we choose 50 bees as a swarm size, in the onlooker phase the probability

of bee placement for a food source will be 1/50; however, if the swarm size is determined as 100 bees, the probability will decrease to 1/100 for an onlooker bee. In this way, the ABC algorithm can prevent agglomerating bees in the same food source and allow wider multiple searches.

First experimental results for parameter settings were run to determine parameter values .Fig. 20.A, 20.B, 20.C, 21.A, and 21.B illustrate results of applied parameter values to compare different cases to determine the best on. Aforementioned five figures (20.A-21.B) show the wastage change as focal point of this study to be optimised, throughout experimental run represented as number of iteration. In this study, the swarm size is determined as 50 and 100. According to Table 1, the results of a 100 bee swarm based search are slightly better than a 50 bee swarm based search in the same conditions; however, the consumed time is approximately doubled in a 100 bee swarm based search. On the other hand, according to Table 2, a 50 bee swarm based search obtained better solutions probably because of the randomisation characteristic.

Table 1: Experiment Results for Dataset-4 Group-7

Swarm:100	Iteration:500		Max Number of Fail:5		Minimum Bin Usage Ratio:0.50		Group:7		Optimum Number of Bin:395								
Test	1		2		3		4		5		OVERALL						
Time(sc	693.8073		689.9769		689.1177		692.594		691.9552		BIN				WASTE			
	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Best	No.Best	Mean	St. Dev.	Best	No.Best	Mean	St. Dev.
Best	414	0.048	414	0.048	412	0.043	416	0.053	416	0.052	412	1	414.4	1.6733	0.0432	1	0.0488	0.0040
Mean	448	0.12	447.4	0.119	449.3	0.122	448.6	0.121	449.1	0.122	447.4	1	448.5	0.7757	0.1188	1	0.1206	0.0014
St. Dev.	15.32	0.03	11.26	0.023	14.79	0.028	13.46	0.026	15.69	0.03	11.26	1	14.10	1.7978	0.0227	1	0.0273	0.0031
Swarm:50	Iteration:500		Max Number of Fail:5		Minimum Bin Usage Ratio:0.50		Group:7		Optimum Number of Bin:395								
Test	1		2		3		4		5		OVERALL						
Time(sc	341.7189		341.4308		340.1266		339.423		353.763		BIN				WASTE			
	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Best	No.Best	Mean	St. Dev.	Best	No.Best	Mean	St. Dev.
Best	417	0.055	415	0.051	418	0.058	416	0.053	420	0.062	415	1	417.2	1.9235	0.0507	1	0.0557	0.0046
Mean	452.6	0.129	450.6	0.124	449.8	0.123	449.5	0.123	453.4	0.13	449.50	1	451.18	1.7184	0.1225	1	0.1257	0.0034
St. Dev.	15.8	0.029	17.69	0.033	15.49	0.03	15	0.029	14.69	0.027	14.69	1	15.74	1.1749	0.0271	1	0.0296	0.0023

Table 2: Experiment Results for Dataset-4 Group-1

Swarm:100	Iteration:500		Max Number of Fail:5		Minimum Bin Usage Ratio:0.50		Group:1		Optimum Number of Bin:399								
Test	1		2		3		4		5		OVERALL						
Time(sc	701.4516		696.7381		702.8945		701.7984		698.6498		BIN				WASTE			
	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Best	No.Best	Mean	St. Dev.	Best	No.Best	Mean	St. Dev.
Best	421	0.054	422	0.056	422	0.056	420	0.052	421	0.054	420	1	421.2	0.8367	0.0520	1	0.0542	0.0017
Mean	455.9	0.126	454.7	0.124	454.6	0.123	456.6	0.127	453.3	0.121	453.3	1	455	1.3024	0.1207	1	0.1240	0.0025
St. Dev.	15.71	0.029	14.04	0.027	12.91	0.025	13.41	0.025	11.69	0.023	11.689	1	13.554	1.4831	0.0231	1	0.0260	0.0024
Swarm:50	Iteration:500		Max Number of Fail:5		Minimum Bin Usage Ratio:0.50		Group:1		Optimum Number of Bin:399								
Test	1		2		3		4		5		OVERALL						
Time(sc	340.6219		347.4818		348.2668		348.7814		345.602		BIN				WASTE			
	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Best	No.Best	Mean	St. Dev.	Best	No.Best	Mean	St. Dev.
Best	423	0.059	419	0.049	423	0.059	418	0.047	419	0.05	418	1	420.4	2.4083	0.0474	1	0.0528	0.0056
Mean	453.8	0.122	455.1	0.124	456	0.126	454.3	0.123	454.8	0.123	453.82	1	454.80	0.8390	0.1217	1	0.1234	0.0015
St. Dev.	13.74	0.026	15.16	0.029	15.57	0.029	12.83	0.025	15.68	0.03	12.831	1	14.597	1.2547	0.0249	1	0.0279	0.0022

These two tables show that there is no clue whether bee size affects the results or not; however, at least it is assured that the algorithm makes a deeper search with a 100 bee swarm parameter. On the other hand, wider swarm could be determined but the consumed time will be increased by assigning a higher number of bees. As a result, in this study a 100 bee swarm is determined as the default parameter value.

The number of iterations is also an important parameter for a search because little iteration can mislead us about the outputs of experiments. On the other hand, researchers should avoid an unnecessary number of iterations to save time.

In this study, various experiments were run to determine the default parameter value for the number of iterations. Dataset-4 (the widest dataset in this study to process with 1000 items) is considered due to its size because it requires more iteration to make the result graph reach a stable condition. Fig. 20.A, 20.B and 20.C show the tendency of the result. In Fig. 20.A; the graph does not reach its stability with 5,000 iterations; however, in Fig. 20.C; 10,000 iterations was tried and the graph reaches its approximate stability. Finally, 7,500 iterations were tried and in Fig. 20.C the result also reached its approximate stability. As a result, in this study, 7,500 iterations is determined as the default parameter value and applied for all datasets.

Another parameter of experiments is the number of failure allowance for neighbourhood search performed by bees. If a small number of failure allowances are determined as a default value, bees cannot perform a further neighbourhood search around the source in the ABC algorithm and cannot find possible better solutions. On the other hand, if a high number of failure allowances are determined, bees do not seek another source and it may cause unnecessary time consumption.

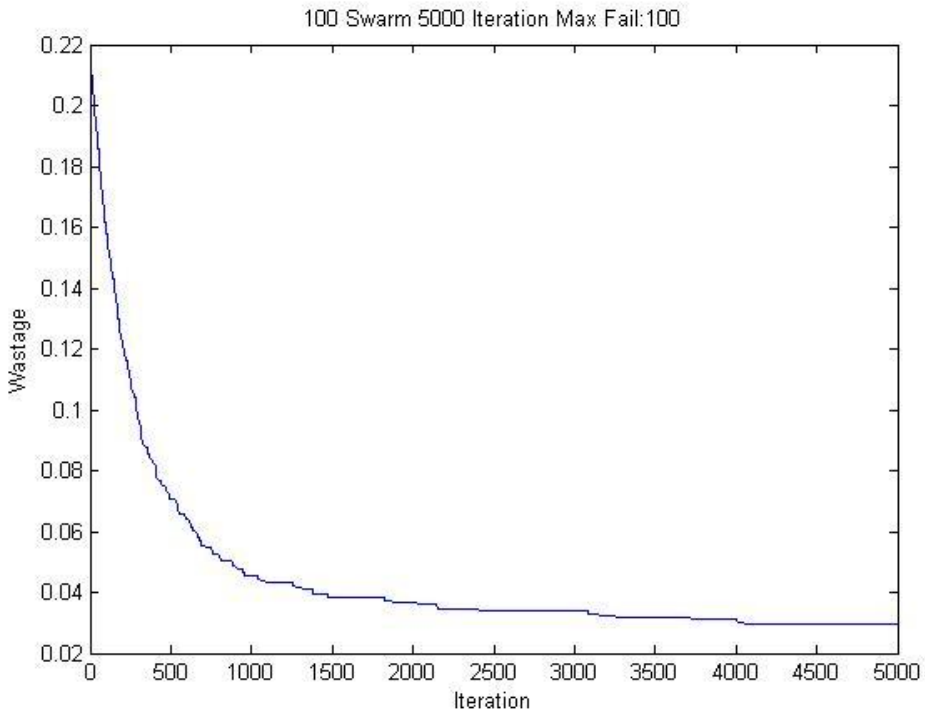


Fig. 20.A: 5000 Iteration Experiment for Dataset-4 Group-7

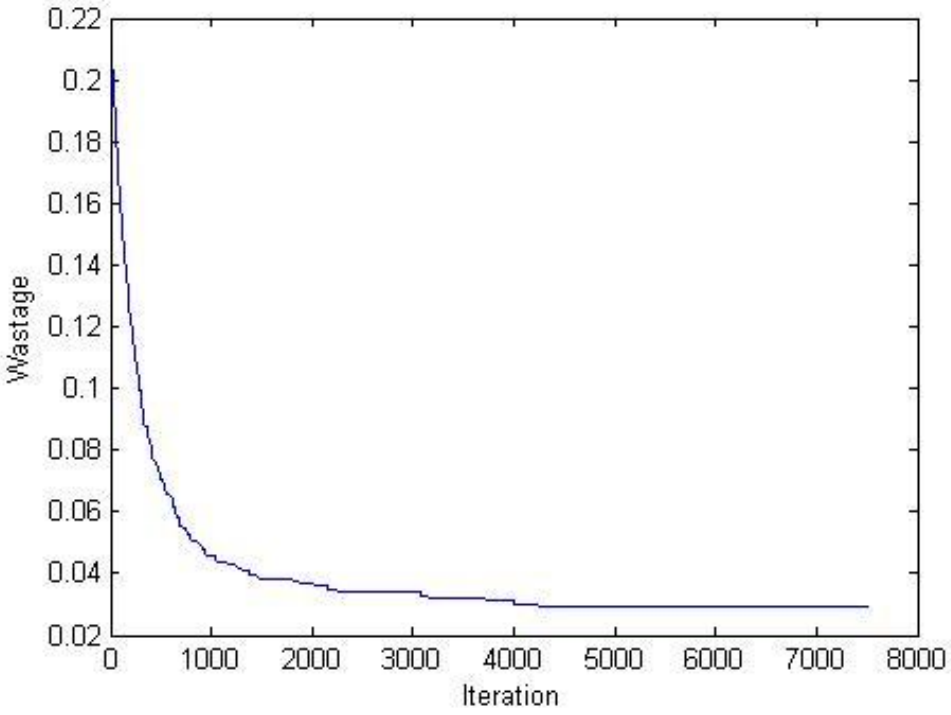


Fig. 20.B: 7500 Iteration Experiment for Dataset-4 Group-7

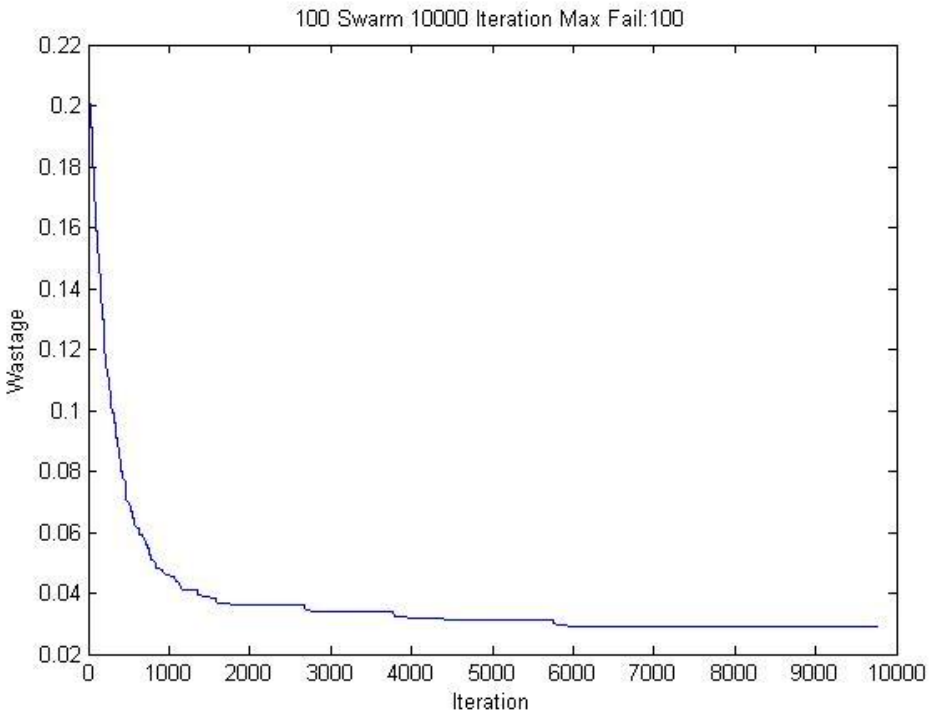


Fig. 20.C: 10000 Iteration Experiment for Dataset-4 Group-7

In this study, as a first step the number of failure allowances is determined as 3 and 5 as shown in table-1 and table-2; however, a further search by applying a higher number of failures shows that, the applied algorithm requires a higher allowance to obtain better solutions. The effect of a high number can be observed even in comparison between 3 and 5 allowance as shown in table-3.

Table 3: The Effect of the Number of Failure Allowance in Same Group in Dataset-4

Swarm:100 Iteration:500 Max Number of Fail:5 Minimum Bin Usage Ratio:0.50 Group:17 Optimum Number of Bin:404																		
Test	1		2		3		4		5		OVERALL							
Time(sc	701.9968		700.6699		703.7574		702.5691		703.1147		BIN				WASTE			
	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Best	No.Best	Mean	St. Dev.	Best	No.Best	Mean	St. Dev.
Best	424	0.0504	427	0.0561	422	0.045	429	0.0605	426	0.0539	422	1	425.6	2.7019	0.0450	1	0.0532	0.0059
Mean	463.98	0.1311	463.34	0.1298	464.3	0.1316	462.25	0.1277	462.36	0.128	462.25	1	463.25	0.9268	0.1277	1	0.1296	0.0018
St. Dev.	13.035	0.0246	14.525	0.0277	14.392	0.027	12.767	0.0247	13.982	0.0268	12.7670	1	13.7402	0.7974	0.0246	1	0.0262	0.0014
Swarm:100 Iteration:500 Max Number of Fail:3 Minimum Bin Usage Ratio:0.50 Group:17 Optimum Number of Bin:404																		
Test	1		2		3		4		5		OVERALL							
Time(sc	677.7256		680.6866		678.7537		682.1542		681.7967		BIN				WASTE			
	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Best	No.Best	Mean	St. Dev.	Best	No.Best	Mean	St. Dev.
Best	433	0.0703	429	0.0609	426	0.0547	433	0.0692	432	0.068	426	1	430.6	3.0496	0.0547	1	0.0646	0.0067
Mean	470.68	0.1428	470.39	0.1422	469.74	0.141	470.57	0.1429	474.13	0.149	469.74	1	471.1	1.7315	0.1410	1	0.1436	0.0031
St. Dev.	18.15	0.0321	19.003	0.0337	19.383	0.0345	16.609	0.0293	19.561	0.034	16.6085	1	18.5412	1.2095	0.0293	1	0.0327	0.0021

The average optimum number of bins with 5 failure allowance in group-17 is 425.60; however, it increased to 430.60 when the number of failures was determined as 3. Fig. 21.A and 21.B also show the effect of failure allowance determined as 100 and 1000 respectively with 5,000 iterations.

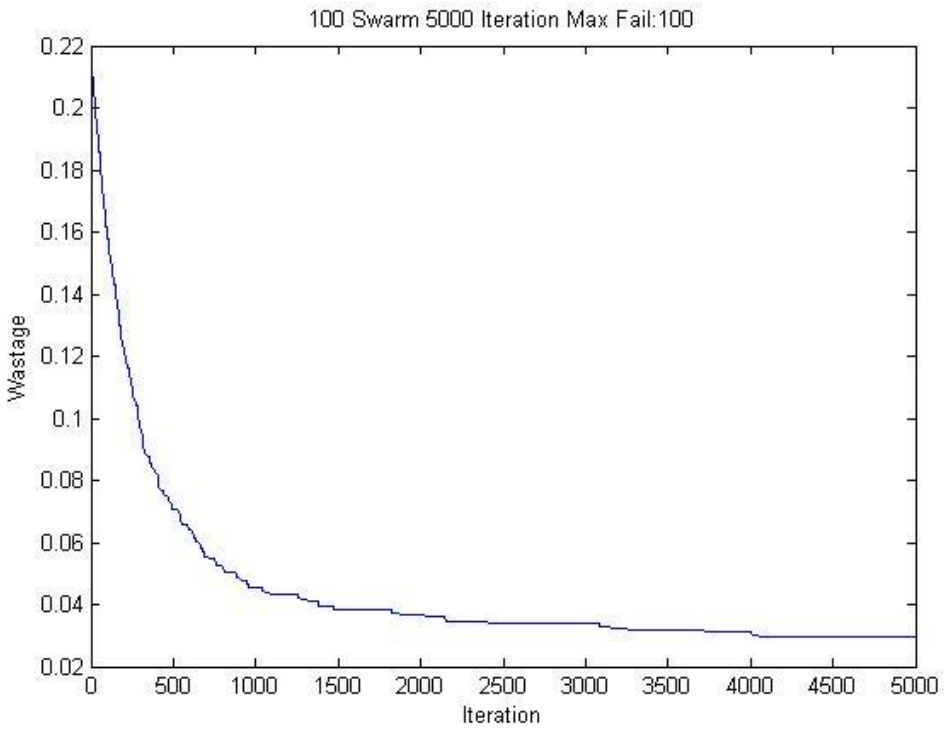


Fig. 21.A: 100 Failure Experiment for Dataset-4 Group-7

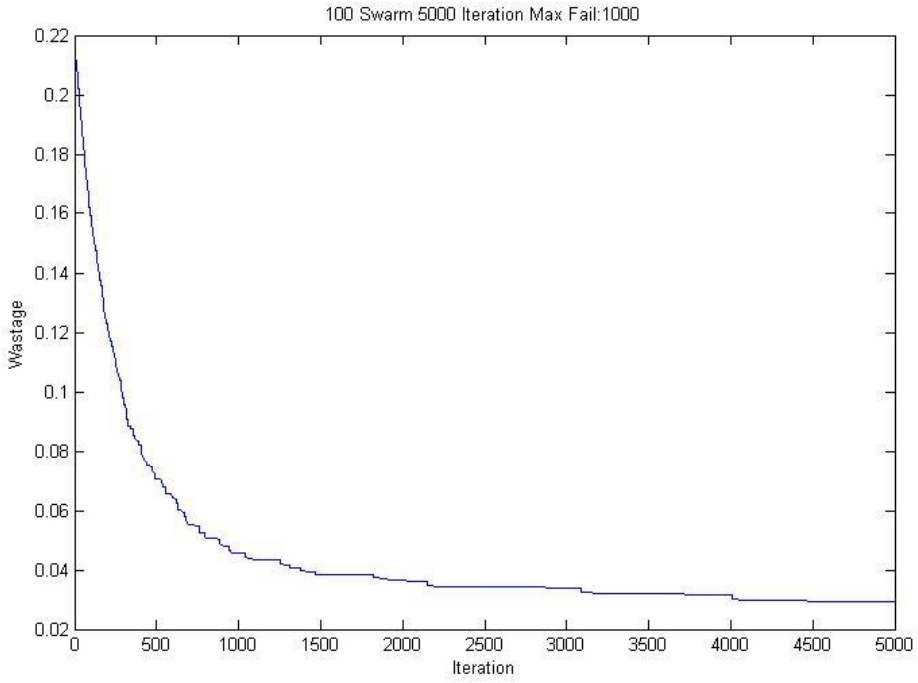


Fig. 21.B: 1,000 Failure Allowance Experiment for Dataset-4 Group-7

Throughout 5,000 iterations, the ABC algorithm search obtains the same minimum value of 0.0295; however, the 50 failure allowance experiment obtains a worse result with 0.0315. According to

table-3 and Fig. 21.A and 21.B results improve while the number of maximum failures increases until 100 failures. Over this value, the ABC algorithm cannot show a significant difference. As a result, the number of maximum failures is determined as 100.

The last important parameter is the period of an item saved in the tabu list. In fact, various tabu periods were tried for experiments yet there is no significant better solution in comparison with the traditional ABC algorithm and very few solutions are saved in memory. On the other hand, we need to observe the effect of the tabu list on experiments and investigate the tendency of the proposed approach by the agency of result graphs.

In this study, the length of the period is determined as 1500 iterations which equal 20% of the total number of iterations.

4.3 Experimental Results

There are 8 item-sets which consist of 120, 250, 500, 1000, 60, 120, 249, and 501 items respectively. Experiments were executed in three phases: traditional algorithm results, classic ABC algorithm results, and memory embedded ABC algorithm results.

In following pages in this part; whole figures represent experimental results of applied algorithms by graphs for 8 different item-sets. Results are introduced by average number of bins and average wastage change throughout experimental runs represented as number of iteration.

4.3.1 Results for Traditional Algorithms

In the first phase, 5 different traditional algorithms were applied on all sub-groups of item-sets. Each item-set consists of 20 sub-groups. Results of the first four item-sets and second four item-sets show different attitudes due to their distribution and integrity characteristics. Only two of the eight item-sets are demonstrated in table-4.A and table-4.B for the raw results of traditional 1-D bin packing algorithms. The rest of traditional 1-D bin packing results can be seen in Appendix A between page 84 and 91 by eight different tables.

Yellow highlighted rows represent randomly chosen sub-groups shown at the left side of tables, for implementation in second and last phase. “LS” represents list size of sub-groups and “Cap.” represents the capacity of bins. At the top of results, applied algorithms are illustrated in green boxes. Wastage values for best solutions are not provided because the website [55] only provides the best number of bins.

Table-4.A: Results of Traditional 1-D Bin Packing Algorithms for Itemset-4

Data Set (LS:1000 Cap:150)	First-Fit		Next-Fit		Best-Fit		Worst-Fit		Best-Fit Decreasing		Best Solution
	#Bin	Waste	#Bin	Waste	#Bin	Waste	#Bin	Waste	#Bin	Waste	#Bin
1	420	0.0514	522	0.2367	419	0.0491	500	0.2031	403	0.0113	399
2	427	0.0509	534	0.2411	426	0.0487	512	0.2085	411	0.014	406
3	433	0.0527	545	0.2473	432	0.0505	520	0.2112	416	0.0139	411
4	435	0.0555	542	0.2419	434	0.0533	517	0.2053	416	0.0123	411
5	419	0.0531	521	0.2385	418	0.0509	495	0.1985	402	0.0131	397
6	421	0.0535	532	0.251	419	0.0489	498	0.1998	404	0.0136	399
7	416	0.0524	517	0.2375	415	0.0501	490	0.1955	399	0.012	395
8	426	0.0536	530	0.2393	425	0.0514	502	0.1969	408	0.0119	404
9	419	0.0491	531	0.2497	418	0.0468	498	0.1999	404	0.0138	399
10	418	0.0504	523	0.2411	419	0.0527	490	0.1899	404	0.0175	397
11	420	0.0492	528	0.2437	419	0.0469	498	0.1981	404	0.0115	400
12	423	0.0531	527	0.24	422	0.0509	497	0.1941	405	0.0111	401
13	414	0.0526	519	0.2442	411	0.0456	483	0.1879	398	0.0145	393
14	415	0.0475	517	0.2354	414	0.0452	491	0.195	401	0.0143	396
15	415	0.0509	517	0.2381	414	0.0486	492	0.1994	400	0.0153	394
16	422	0.0479	530	0.2419	423	0.0501	506	0.2059	408	0.0152	402
17	425	0.0517	531	0.241	425	0.0517	508	0.2066	407	0.0098	404
18	422	0.0431	535	0.2452	423	0.0454	507	0.2036	409	0.0127	404
19	419	0.0497	526	0.243	419	0.0497	498	0.2004	403	0.0119	399
20	421	0.0515	521	0.2335	419	0.0469	495	0.1933	406	0.0164	400
MEAN	421.5	0.0510	527.4	0.2415	420.7	0.0492	499.85	0.1996	405.4	0.0133	400.55
STANDART DEVIATION	4.9044	0.0029	6.9056	0.0044	5.1973	0.0025	7.9793	0.0052	4.2060	0.0020	4.3400

Table-4.B: Results of Traditional 1-D Bin Packing Algorithms for Itemset-8

Data Set (LS:501 Cap:100)	First-Fit		Next-Fit		Best-Fit		Worst-Fit		Best-Fit Decreasing		Best Solution
	#Bin	Waste	#Bin	Waste	#Bin	Waste	#Bin	Waste	#Bin	Waste	#Bin
1	178	0.0618	196	0.148	178	0.0618	184	0.0924	190	0.1211	167
2	181	0.0773	200	0.165	180	0.0722	186	0.1022	191	0.1257	167
3	178	0.0618	194	0.1392	178	0.0618	186	0.1022	190	0.1211	167
4	178	0.0618	196	0.148	178	0.0618	188	0.1117	191	0.1257	167
5	178	0.0618	194	0.1392	179	0.067	185	0.0973	191	0.1257	167
6	178	0.0618	194	0.1392	178	0.0618	182	0.0824	190	0.1211	167
7	178	0.0618	197	0.1523	178	0.0618	185	0.0973	190	0.1211	167
8	179	0.067	199	0.1608	179	0.067	187	0.107	189	0.1164	167
9	178	0.0618	199	0.1608	178	0.0618	190	0.1211	191	0.1257	167
10	178	0.0618	191	0.1257	178	0.0618	183	0.0874	190	0.1211	167
11	179	0.067	192	0.1302	179	0.067	184	0.0924	190	0.1211	167
12	177	0.0565	196	0.148	177	0.0565	184	0.0924	190	0.1211	167
13	179	0.067	204	0.1814	179	0.067	194	0.1392	190	0.1211	167
14	179	0.067	195	0.1436	179	0.067	183	0.0874	190	0.1211	167
15	180	0.0722	195	0.1436	179	0.067	184	0.0924	189	0.1164	167
16	180	0.0722	197	0.1523	179	0.067	186	0.1022	191	0.1257	167
17	178	0.0618	198	0.1566	178	0.0618	189	0.1164	189	0.1164	167
18	180	0.0722	200	0.165	179	0.067	187	0.107	191	0.1257	167
19	179	0.067	202	0.1733	179	0.067	186	0.1022	189	0.1164	167
20	178	0.0618	197	0.1523	178	0.0618	185	0.0973	191	0.1257	167
MEAN	178.65	0.0652	196.8	0.1512	178.5	0.0644	185.9	0.1015	190.15	0.1218	167
STANDART DEVIATION	0.8444	0.0044	3.2582	0.0140	0.6057	0.0032	2.9105	0.0138	0.7579	0.0035	0.0000

In table 4.A, the best average result among the aforementioned traditional algorithms is obtained by the best-fit decreasing (BFD) algorithm. On the other hand, the BFD algorithm cannot show the same performance in table 4.B and it is beaten by the best-fit (BF) algorithm.

4.3.2 Results for Classic Artificial Bee Colony Algorithm

In the second and last phase of experiment execution, only randomly chosen five yellow highlighted sub-groups of item-sets are progressed because of their much longer run time in comparison with traditional algorithm experiments. In this chapter, only one of the chosen five sub-groups is demonstrated for each item-set result. Firstly, the results of the classic ABC algorithm are shown with tables and graphs in figures. A large form of the result tables and graphs can be seen in appendices.

Table 5.A: Results of Classic ABC Algorithm for Itemset-1 Group-1

Swarm:100 Iteration:7500 Max Number of Fail:100 Minimum Bin Usage Ratio:0.50 Group:1 Optimum Number of Bin:48																		
Test	1		2		3		4		5		OVERALL							
Time(sc)	939.0273		936.5731		936.2996		935.5605		934.8444		BIN				WASTE			
	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Best	No.Best	Mean	St. Dev.	Best	No.Best	Mean	St. Dev.
Best	49	0.037	48	0.0228	48	0.0226	48	0.0226	48	0.0222	48	4	48.2	0.4472	0.0222	1	0.0254	0.0065
Mean	49.038	0.0378	48.9813	0.0372	48.9485	0.0367	48.5109	0.0326	48.9624	0.0368	48.5109	1	48.8882	0.2137	0.0326	1	0.0362	0.0021
St. Dev.	0.3575	0.0067	0.4581	0.0079	0.4625	0.0079	0.6929	0.01	0.4721	0.0081	0.3575	1	0.4886	0.1233	0.0067	1	0.0081	0.0012

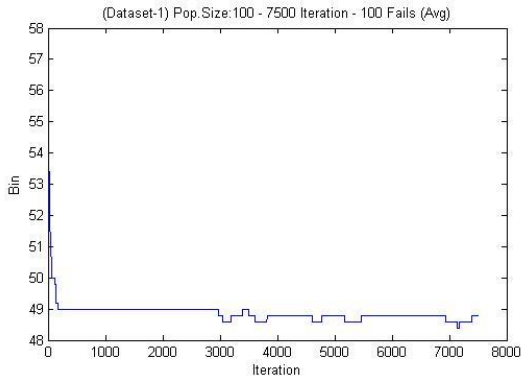


Fig. 22.A: Average Number of Bins Graph for Table 5.A

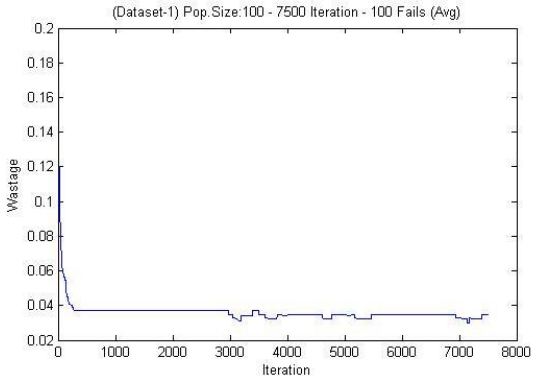


Fig. 22.B: Average Wastage Graph for Table 5.A

Fig. 22.A and Fig. 22.B show the improvement of obtained results average by number of bins and wastage level respectively shown in table 5.A throughout the search process. The number of bins and wastage level reduce sharply in the early period of the process. The best solution is obtained approximately at the end of the process. Rest of results for sub-groups (Appendix B page 93-97) of

Itemset-1 show same attitudes with graphs in Fig. 22.A and Fig. 22.B but the obtained number of bins because of total value of items in sub-groups.

Table 5.B: Results of Classic ABC Algorithm for Itemset-2 Group-5

Swarm:100 Iteration:7500 Max Number of Fail:100 Minimum Bin Usage Ratio:0.50 Group:5 Optimum Number of Bin:101																		
Test	1		2		3		4		5		OVERALL							
Time(sc)	2.20E+03		2.20E+03		2.15E+03		2.27E+03		2.13E+03		BIN				WASTE			
	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Best	No.Best	Mean	St. Dev.	Best	No.Best	Mean	St. Dev.
Best	103	0.0256	103	0.0249	103	0.0256	103	0.0256	103	0.0256	103	5	103	0.0000	0.0249	1	0.0255	0.0003
Mean	103.35	0.0329	103.33	0.0327	103.35	0.0329	103.35	0.0329	103.35	0.0329	103.33	1	103.346	0.0089	0.0327	1	0.0329	0.0001
St. Dev.	0.5416	0.0053	0.4136	0.0041	0.5416	0.0053	0.5416	0.0053	0.5416	0.0053	0.4136	1	0.5160	0.0572	0.0041	1	0.0051	0.0005

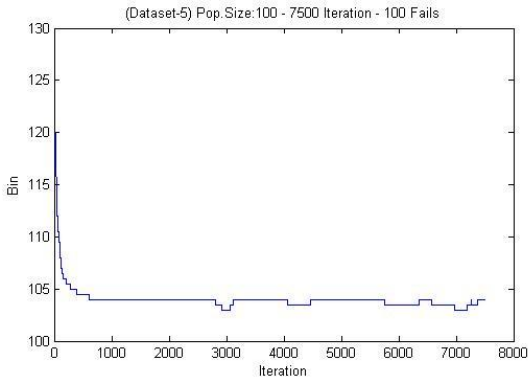


Fig. 23.A: Average Number of Bins Graph for Table 5.B

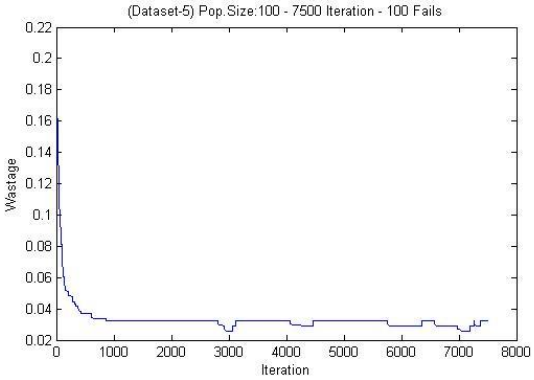


Fig. 23.B: Average Wastage Graph for Table 5.B

The tendency of Fig. 23.A and Fig. 23.B show the same attitudes with Fig. 22.A and Fig. 22.B; however, it takes more time to reach stability probably because of the size of the item-set. Besides, the search obtains the best solution at iteration 3000 approximately conversely results of other sub-groups of itemset-2 (Appendix B page 98-102) because other sub-groups obtain the best results before 3000 iteration.

The experiment groups were executed once in itemset-3, itemset-4, and itemset-8 because the run times are too long and according to the aim of the graphs, obtained results can be considered as average results. The results of the aforementioned item-sets are demonstrated in table 5.C.

Table 5.C: Results of Classic ABC Algorithm for Itemset-3, Itemset-4, and Itemset-8

			BIN	WASTAGE (%)	TIME (sec)
ABC	IS-3 Gr-3	100-7500-100	207	0.0280	5.8826e+03
ABC	IS-4 Gr-1	100-7500-100	411	0.0306	1.4936e+04
ABC	IS-8 Gr-8	100-7500-100	175	0.0473	6.1104e+03

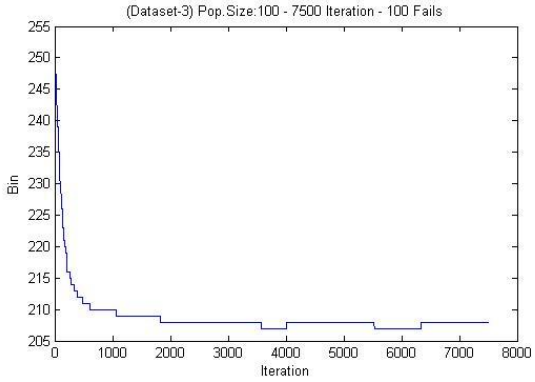


Fig. 24.A: Average No. of Bins Graph for IS-3 in Table 5.C

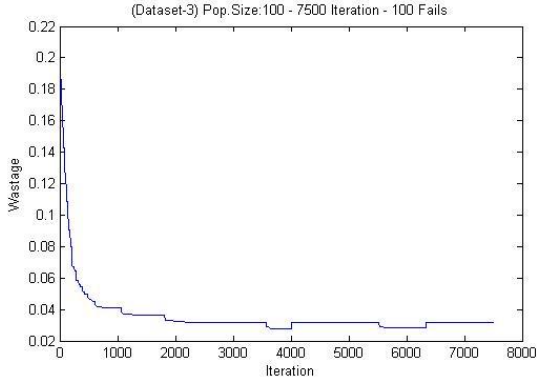


Fig. 24.B: Average Wastage Graph for IS-3 in Table 5.C

According to Fig. 24.A and Fig. 24.B, the search process reaches its stability at iteration 2000 approximately and shows a more proper presentation in comparison with the previous two item-sets by a reduction in the number of zig zags. The search obtains its best result at the mid-process.

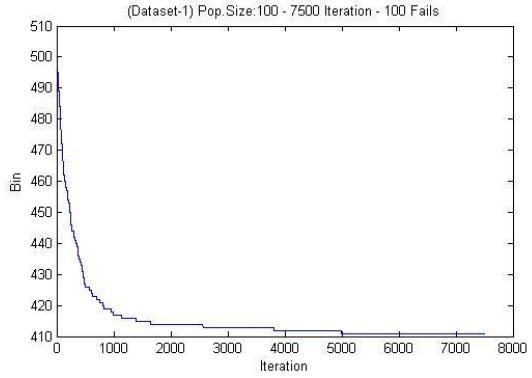


Fig. 25.A: Average No. of Bins Graph for IS-4 in Table 5.C

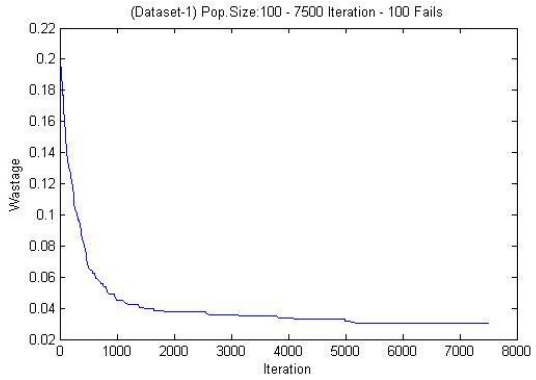


Fig. 25.B: Average Wastage Graph for IS-4 in Table 5.C

The most proper graphs in the first four item-sets with much fewer zig zags are Fig. 25.A and Fig. 25.B. As seen in the graphs, they reach their stable condition later than others because the item exchange rate in wide sized item-set is smaller than others and this exchange may not be observed in graphs. Even 7500 iterations would not be enough to find the algorithm's best solution because the stable condition cannot be observed for a long period.

Table 5.D: Results of Classic ABC Algorithm for Itemset-5 Group-2

Swarm:100 Iteration:7500 Max Number of Fail:100 Minimum Bin Usage Ratio:0.50 Group:2 Optimum Number of Bin:20																		
Test	1		2		3		4		5		OVERALL							
Time(sc)	457.2261		462.4832		461.3166		469.2675		472.8706		BIN				WASTE			
	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Best	No.Best	Mean	St. Dev.	Best	No.Best	Mean	St. Dev.
Best	21	0.0476	21	0.0476	21	0.0476	20	0.0198	21	0.0476	20	1	20.8	0.4472	0.0198	1	0.0420	0.0124
Mean	21.0013	0.0478	21.0021	0.0478	21.0021	0.0478	20.9887	0.0474	21.0021	0.0478	20.9887	1	20.9993	0.0059	0.0474	1	0.0477	0.0002
St. Dev.	0.0462	0.0025	0.0541	0.0027	0.0541	0.0027	0.1286	0.0042	0.0516	0.0025	0.0462	1	0.0669	0.0346	0.0025	2	0.0029	0.0007

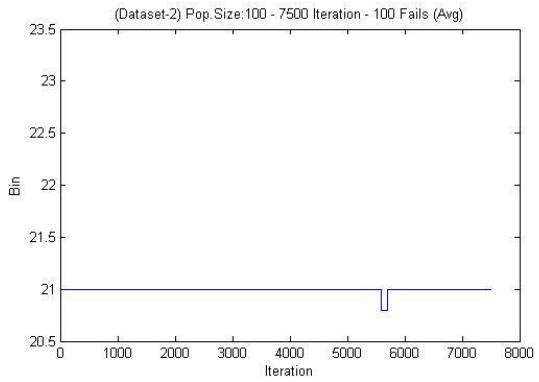


Fig. 26.A: Average Number of Bins Graph for Table 5.D

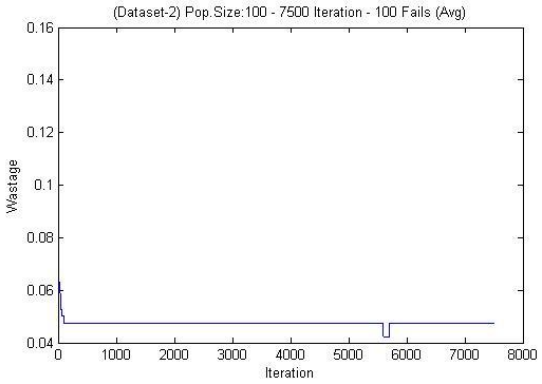


Fig. 26.B: Average Wastage Graph for Table 5.D

Both Fig. 26.A and Fig. 26.B show that the search for 60-variable-item-set seems to reach an optimum solution at the beginning of the process; however, the obtained solution is only a local optimum and it means that in some cases the global optimum might be obtained by further searching.

Table 5.E: Results of Classic ABC Algorithm for Itemset-6 Group-2

Swarm:100 Iteration:7500 Max Number of Fail:100 Minimum Bin Usage Ratio:0.50 Group:2 Optimum Number of Bin:40																		
Test	1		2		3		4		5		OVERALL							
Time(sc)	916.9337		917.1444		912.4433		910.5781		919.3476		BIN				WASTE			
	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Best	No.Best	Mean	St. Dev.	Best	No.Best	Mean	St. Dev.
Best	42	0.0476	42	0.0476	41	0.0348	42	0.0476	42	0.0476	41	1	41.8	0.4472	0.0348	1	0.0451	0.0057
Mean	42.016	0.0481	42.0107	0.0479	42.005	0.0479	42.0107	0.0479	42.016	0.0481	42.0053	1	42.0117	0.0045	0.0479	1	0.0480	0.0001
St. Dev.	0.2123	0.0048	0.1808	0.0040	0.2122	0.0045	0.1808	0.0040	0.2123	0.0048	0.1808	2	0.1997	0.0172	0.0040	2	0.0044	0.0004

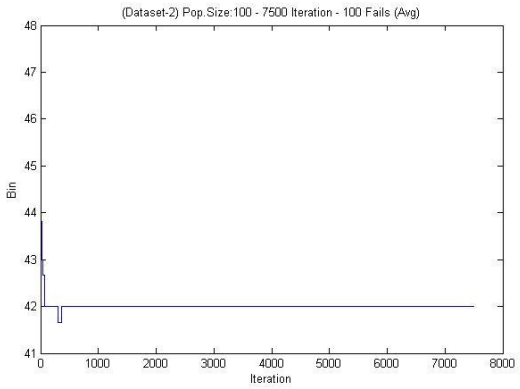


Fig. 27.A: Average Number of Bins Graph for Table 5.E

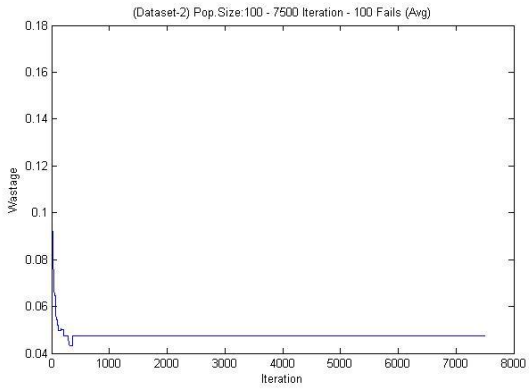


Fig. 27.B: Average Wastage Graph for Table 5.E

In contradistinction to Fig. 26.A and Fig. 26.B, in Fig. 27.A and Fig. 27.B; graphs obtain their best solution in the early period of the process. However, the graph reaches a stable condition with worse solution and never obtains the best solution again. Graphs of other sub-groups of itemset-6 (Appendix B page 114-118) show same attitudes but change characteristic. They also obtain best solution in early period however; they reach stabile condition in late period with more zig zags.

Table 5.F: Results of Classic ABC Algorithm for Itemset-7 Group-1

Swarm:100 Iteration:7500 Max Number of Fail:100 Tabu Period:1500 Minimum Bin Usage Ratio:0.50 Group:1 Optimum Number of Bin:83																		
Test	1		2		3		4		5		OVERALL							
Time(sc)	1.99E+03		2.00E+03		1.85E+03		1.96E+03		1.95E+03		BIN				WASTE			
	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Best	No.Best	Mean	St. Dev.	Best	No.Best	Mean	St. Dev.
Best	88	0.0568	87	0.0510	88	0.0574	88	0.0578	87	0.0584	87	2	87.6	0.5477	0.0510	1	0.0563	0.0030
Mean	88.056	0.0576	88.0425	0.0574	88.075	0.0587	88.063	0.0579	88.0438	0.0582	88.0425	1	88.0561	0.0136	0.0574	1	0.0580	0.0005
St. Dev.	0.5613	0.0057	0.6108	0.0061	0.5572	0.0057	0.5698	0.0058	0.6188	0.0060	0.5572	1	0.5836	0.0290	0.0057	1	0.0059	0.0002

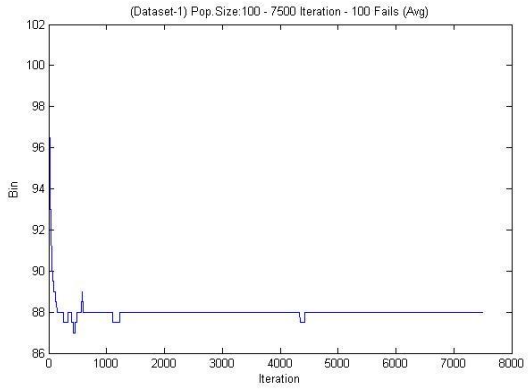


Fig. 28.A: Average Number of Bins Graph for Table 5.F

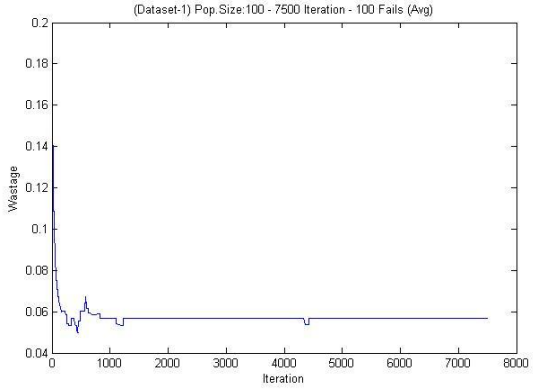


Fig. 28.B: Average Wastage Graph for Table 5.F

Fig. 28.A and Fig. 28.B show the same characteristic as graphs of itemset-6 but a higher number of zig zags.

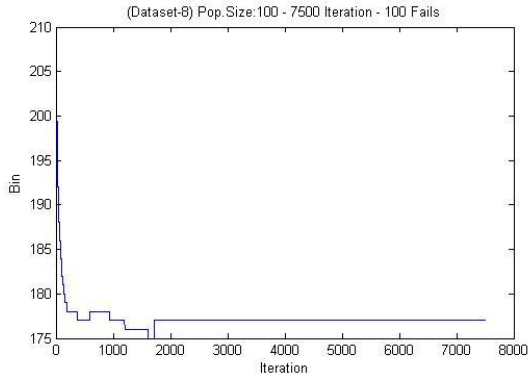


Fig. 29.A: Average No. of Bins Graph for IS8 in Table 5C

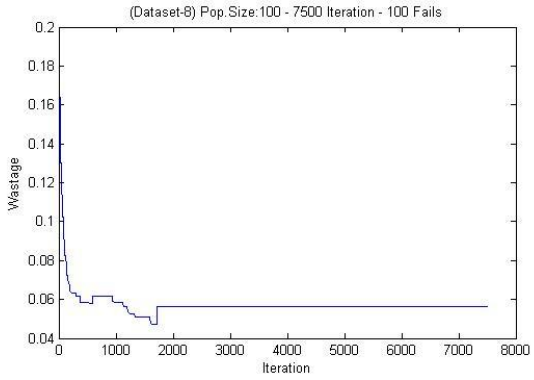


Fig. 29.B: Average Wastage Graph for IS8 in Table 5.C

In Fig. 29.A and Fig. 29.B; graphs obtain the best solution near iteration 2000. Like the previous graphs of the two item-set (6 and 7), the graph for results of itemset-8 achieves stability with a worse solution. The possible reason for this condition is that, in the ABC algorithm we also substitute a new solution instead of the best solution of the current iteration after 100 failures. On the other hand, the algorithm in which we do not replace the best solution of iteration, cannot obtain any better solution in comparison with the current method.

The ABC algorithm search in the second four item-sets obtains the best solution earlier than the first ones due to the distribution difference between them. It means that items in the second four item-sets could be packed easier.

According to the results of the classic ABC algorithm, it is capable of showing a better performance in comparison with traditional 1-D bin packing algorithms; however, the BFD algorithm beats the classic ABC algorithm for first item-sets and obtains the best results. In contrast, the BFD algorithm shows a much worse performance and it is even beaten by the best fit (BF) algorithm which obtains worse results than the classic ABC algorithm for all item-sets.

4.3.3 Results for Memory Embedded Artificial Bee Colony (MEABC) Algorithm

The reason for this condition is probably linked to characteristics of item-sets. As defined above, two different distributed grouped item-sets consist of integer and decimal sized items. Obtained results show that the BFD algorithm cannot show sufficient performance with decimal sized items. The possible reason for this condition is that, if decimal sized items are sorted in a descended trend, items may not be allocated in bins because the same fractioned numbers possibly cannot be assembled easily. On the other hand, different fractioned numbers might be assembled with higher possibility in comparison with the mentioned arrangement. As a next and last step, the results of the proposed memory embedded artificial bee colony (MEABC) algorithm are illustrated in table 6.A.

Table 6.A: Results of Memory Embedded ABC Algorithm for Itemset-1 Group-1

Swarm:100 Iteration:7500 Max Number of Fail:100 Tabu Period:1500 Minimum Bin Usage Ratio:0.50 Group:1 Optimum Number of Bin:48																		
Test	1		2		3		4		5		OVERALL							
Time(sc)	958.1862		957.146		965.2645		954.3279		975.3468		BIN				WASTE			
	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Best	No.Best	Mean	St. Dev.	Best	No.Best	Mean	St. Dev.
Best	48	0.0226	48	0.0228	49	0.037	48	0.0229	48	0.0228	48	4	48.2	0.4472	0.0226	1	0.0256	0.0064
Mean	48.9459	0.0366	48.9873	0.0372	49.0384	0.0379	48.9463	0.0369	48.9868	0.0372	48.9459	1	48.9809	0.0381	0.0366	1	0.0372	0.0005
St. Dev.	0.4886	0.0083	0.4639	0.008	0.3392	0.0064	0.4886	0.0083	0.4639	0.008	0.3392	1	0.4488	0.0625	0.0064	1	0.0078	0.0008

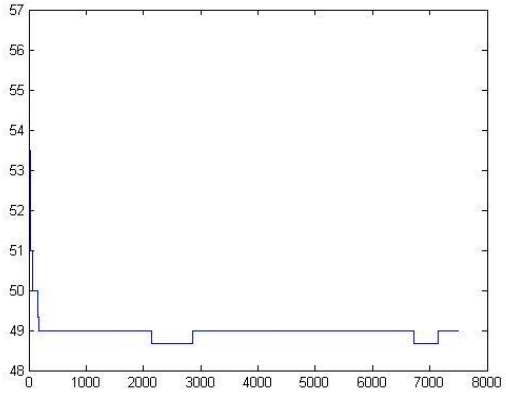


Fig. 30.A: Average Number of Bins Graph for Table 6.A

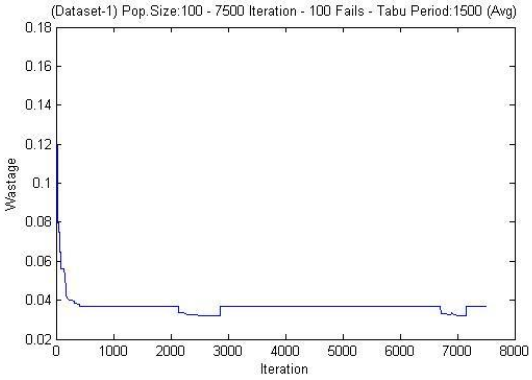
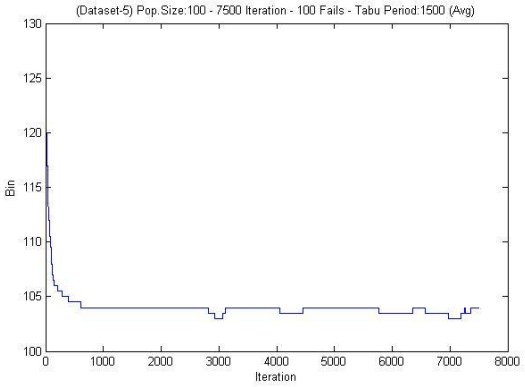


Fig. 30.B: Average Wastage Graph for Table 6.A

According to results in table 6.A, the MEABC algorithm obtains the exact solution like the classic ABC algorithm because of the smallness of the item-set size. This condition changes in next experiments with an increase in wastage level. In Fig. 30.A and 30.B; graphs obtain the best solution of the process at near iteration 1000 and then they are stabilized with a worse solution. Conversely, other sub-groups of itemset-1 (Appendix C page 129-132) reach their stabile condition earlier than sub-group 1 however; sub-group 17 shows sharp change at the end of experiment run. This means that, proposed method may be executed for more iteration.

Table 6.B: Results of Memory Embedded ABC Algorithm for Itemset-2 Group-5

Swarm:100 Iteration:7500 Max Number of Fail:100 Tabu Period:1500 Minimum Bin Usage Ratio:0.50 Group:5 Optimum Number of Bin:101																		
Test	1		2		3		4		5		OVERALL							
Time(sc)	2.53E+03		2.48E+03		2.51E+03		2.51E+03		2.45E+03		BIN				WASTE			
	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Best	No.Best	Mean	St. Dev.	Best	No.Best	Mean	St. Dev.
Best	103	0.0256	103	0.0249	103	0.0256	103	0.0256	103	0.0256	103	5	103	0.0000	0.0249	1	0.0254	0.0003
Mean	104.112	0.0338	104.001	0.0332	104.112	0.0338	104.112	0.0338	104.112	0.0338	104.001	1	104.09	0.0494	0.0332	1	0.0337	0.0003
St. Dev.	1.3931	0.0115	1.4807	0.0123	1.3931	0.0115	1.3931	0.0115	1.3931	0.0115	1.3931	4	1.4106	0.0392	0.0115	4	0.0117	0.0003



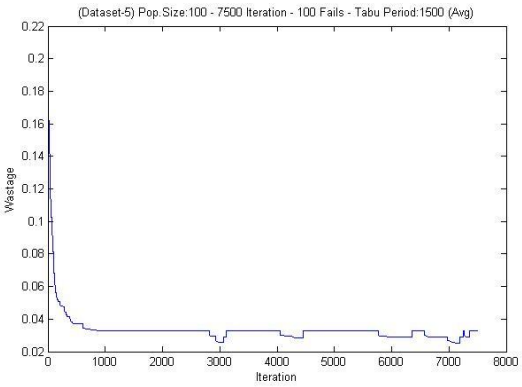
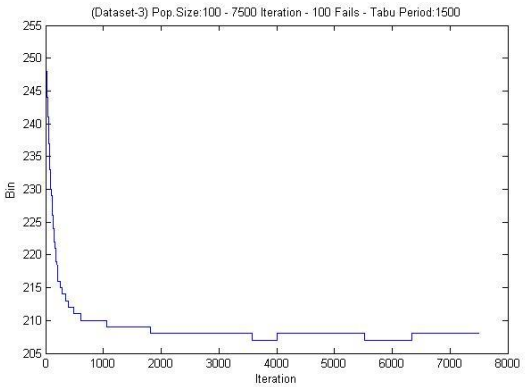


Fig. 31.A: Average Number of Bins for Table 6.B **Fig. 31.B:** Average Wastage for Table 6.B

Like other results, in Fig. 31.A and Fig. 31.B; both graphs tend to achieve stability after an amount of iterations. The straight line of the graphs could be considered as the average of the results if it is achieved in a short time. According to the graphs above, the best solution of the experiment is obtained at near iteration 7000 and then the graphs return to the straight line representing a worse solution after a number of iterations.

Table 6.C: Results of Memory Embedded ABC Algorithm for Itemset-3, Itemset-4, and Itemset-8

			BIN	WASTAGE (%)	TIME (sec)
MEABC	IS-3 Gr-3	100-7500-100	207	0.0280	5.7224e+03
MEABC	IS-4 Gr-1	100-7500-100	411	0.0306	1.4848e+04
MEABC	IS-8 Gr-8	100-7500-100	175	0.0473	6.1104e+03



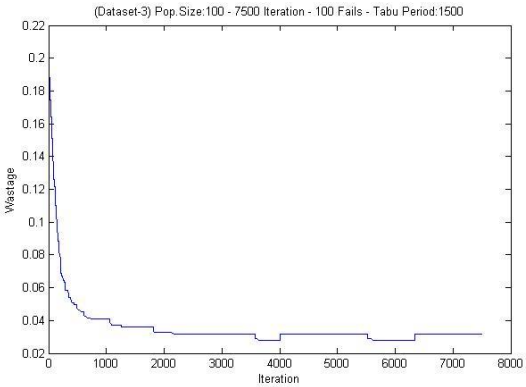


Fig. 32.A: Average No. of Bins Graph for IS3 in Table 6C **Fig. 32.B:** Average Wastage Graph for IS3 in Table 6C

The results of the MEABC algorithm for itemset-3 are the same as the results of the ABC algorithm and the graphs show the same characteristics. It means that the memory system does not affect the ABC algorithm search results. Besides, MEABC results for sub-group 13 (Appendix B, page 93, Table 11) of itemset-3 obtains better solution than classic ABC algorithm as an exception. Itemset-3, itemset-4 and itemset-8 consist of large number of items and run times for them are much longer

than others and because of this circumstance each experiment is run once. In this case, exceptional results are obtained just for aforementioned item-sets because of randomness.

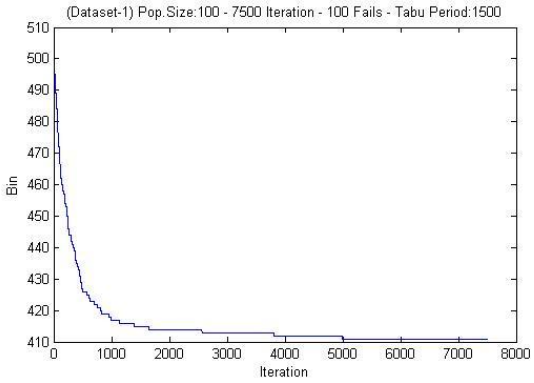


Fig. 33.A: Average No. of Bins Graph for IS4 in Table 6C

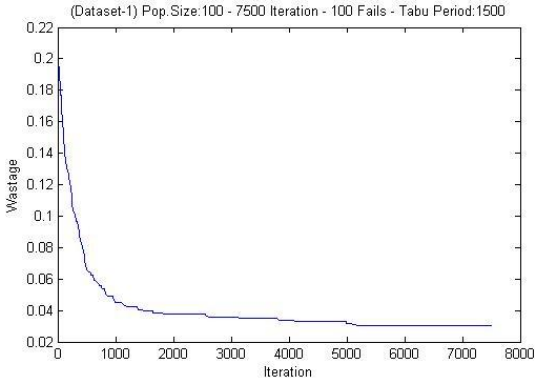


Fig. 33.B: Average Wastage Graph for IS4 in Table 6C

In Fig. 33.A and 33.B; both graphs also show the same performance as the classic ABC algorithm search results and cannot differentiate the obtained results.

Table 6.D: Results of Memory Embedded ABC Algorithm for Itemset-5 Group-2

Swarm:100 Iteration:7500 Max Number of Fail:100 Tabu Period:1500 Minimum Bin Usage Ratio:0.50 Group:2 Optimum Number of Bin:20																		
Test	1		2		3		4		5		OVERALL							
Time(sc)	457.2651		436.4584		456.7254		435.5143		436.4947		BIN				WASTE			
	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Best	No.Best	Mean	St. Dev.	Best	No.Best	Mean	St. Dev.
Best	20	0.0213	21	0.0476	20	0.0232	21	0.0476	20	0.0222	20	3	20.4	0.5477	0.0213	1	0.0324	0.0139
Mean	20.9937	0.0476	21.0019	0.0478	20.9859	0.0473	21.0016	0.0477	20.9701	0.0469	20.9701	1	20.9906	0.0132	0.0469	1	0.0475	0.0003
St. Dev.	0.1147	0.0039	0.0490	0.0025	0.1268	0.0034	0.0490	0.0022	0.1756	0.0048	0.0490	1	0.1030	0.0544	0.0022	1	0.0034	0.0010

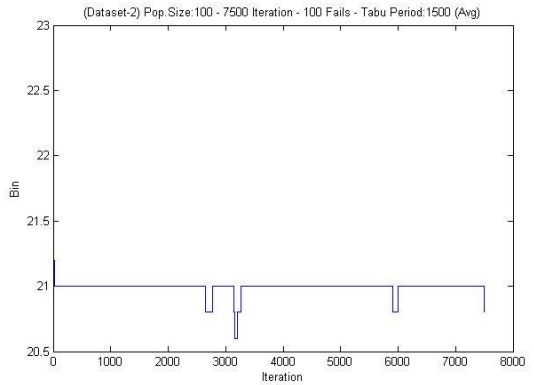


Fig. 34.A: Average Number of Bins Graph for Table 6.D

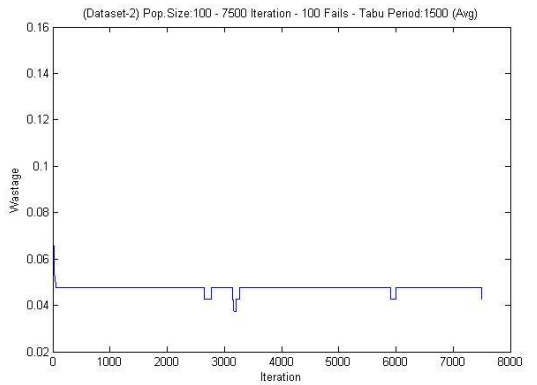


Fig. 34.B: Average Wastage Graph for Table 6.D

The graph of average results for itemset-5 with the MEABC algorithm search is slightly different from the graph of the ABC algorithm search due to the increased number of plunges in the graph. On the other hand, graphs in Fig. 34.A and 34.B can be considered as unstable in comparison with graphs of other sub-groups of itemset-5 (Appendix C page 144-147).

Table 6.E: Results of Memory Embedded ABC Algorithm for Itemset-6 Group-2

Swarm:100 Iteration:7500 Max Number of Fail:100 Tabu Period:1500 Minimum Bin Usage Ratio:0.50 Group:2 Optimum Number of Bin:40																		
Test	1		2		3		4		5		OVERALL							
Time(sc)	1.08E+03		1.06E+03		1.05E+03		1.11E+03		1.05E+03		BIN				WASTE			
	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Best	No.Best	Mean	St. Dev.	Best	No.Best	Mean	St. Dev.
Best	41	0.0347	41	0.0335	41	0.0353	42	0.0476	41	0.0345	41	4	41.2	0.4472	0.0335	1	0.0371	0.0059
Mean	42.2105	0.0535	42.0025	0.0480	42.0047	0.0478	42.0149	0.0481	42.0041	0.0479	42.0025	1	42.0474	0.0913	0.0478	1	0.0491	0.0025
St. Dev.	0.5227	0.0107	0.2414	0.0050	0.2016	0.0043	0.2124	0.0047	0.2318	0.0048	0.2016	1	0.2820	0.1355	0.0043	1	0.0059	0.0027

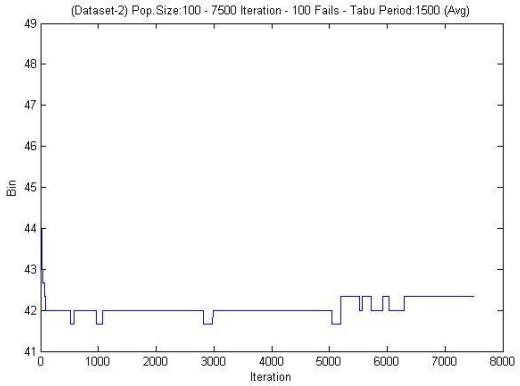


Fig. 35.A: Average Number of Bins Graph for Table 6.E

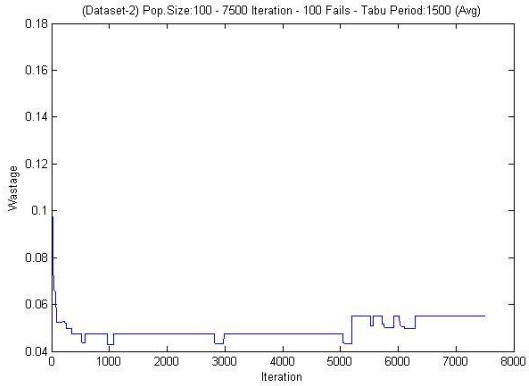


Fig. 35.B: Average Wastage Graph for Table 6.E

In contradistinction to all other graphs, in Fig. 35.A and 35.B; graphs show interesting characteristics with two different straight lines. The trend of the second line observed after iteration 5000 represents a worse solution than the previous worse solution in comparison with the obtained best solution and cannot be fixed until the end of the process. In spite of this, the global optimum is the same as the solution obtained by ABC algorithm search.

Table 6.F: Results of Memory Embedded ABC Algorithm for Itemset-7 Group-1

Swarm:100 Iteration:7500 Max Number of Fail:100 Tabu Period:1500 Minimum Bin Usage Ratio:0.50 Group:1 Optimum Number of Bin:83																		
Test	1		2		3		4		5		OVERALL							
Time(sc)	1.99E+03		2.00E+03		1.85E+03		1.96E+03		1.95E+03		BIN				WASTE			
	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Best	No.Best	Mean	St. Dev.	Best	No.Best	Mean	St. Dev.
Best	88	0.0568	87	0.0510	88	0.0574	88	0.0578	87	0.0584	87	2	87.6	0.5477	0.0510	1	0.0563	0.0030
Mean	88.056	0.0576	88.0425	0.0574	88.075	0.0587	88.063	0.0579	88.0438	0.0582	88.0425	1	88.0561	0.0136	0.0574	1	0.0580	0.0005
St. Dev.	0.5613	0.0057	0.6108	0.0061	0.5572	0.0057	0.5698	0.0058	0.6188	0.0060	0.5572	1	0.5836	0.0290	0.0057	1	0.0059	0.0002

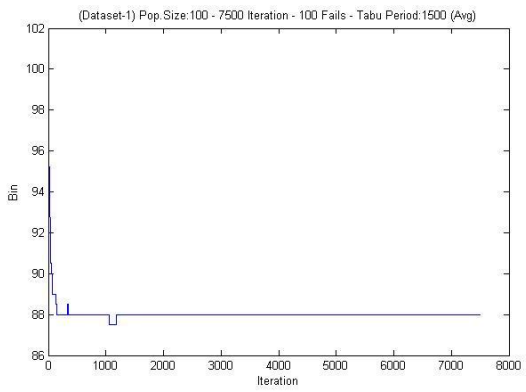


Fig. 36.A: Average Number of Bins Graph for Table 6.F

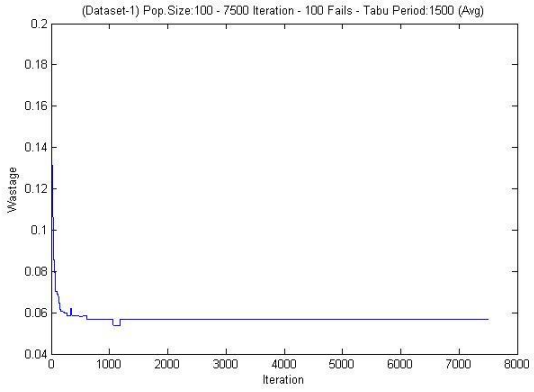


Fig. 36.B: Average Wastage Graph for Table 6.F

The graphs of classic ABC algorithm search and MEABC algorithm search obtain the same optimum solution; however, the MEABC algorithm search reduces the number of instant changes and stabilizes the graph in a shorter time.

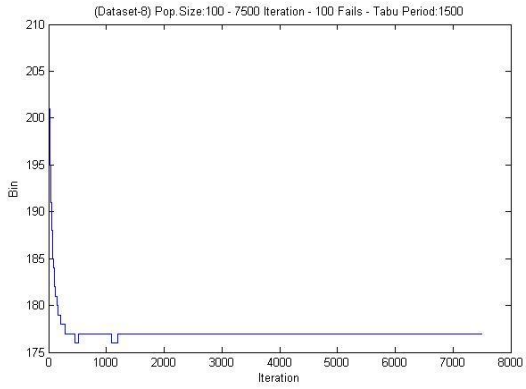


Fig. 37.A: Average No. of Bins Graph for IS8 in Table 6C

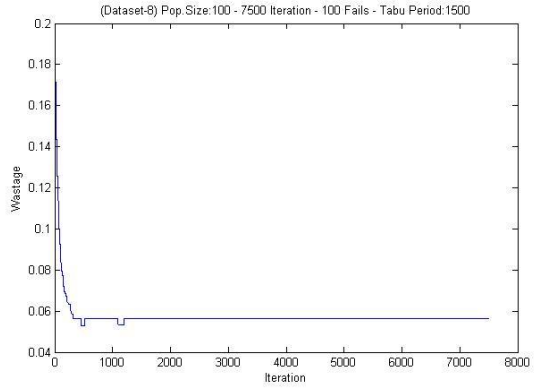


Fig. 37.B: Average Wastage Graph for IS8 in Table 6.C

The MEABC algorithm search obtains a more proper graph than the classic ABC algorithm especially for wide sized item-sets like those shown in Fig. 37.A and Fig. 37.B.

After all results are presented separately, table 7.A and 7.B provide an overview about algorithms using itemset-4 and itemset-8 due to their huge set size because the difference between algorithms cannot be easily observed when algorithms use small sized itemsets. Numbers at the left side of tables represent which sub-group of item-set is used.

Table 7.A: Summary Result Table for Itemset-4

ItemSet 4(LS:1000 Cap:150)	FF		NF		BF		WF		BFD		ABC		MEABC		Best
	#Bin	Waste	#Bin	Waste	#Bin	Waste	#Bin	Waste	#Bin	Waste	#Bin	Waste	#Bin	Waste	#Bin
1	420	0.0514	522	0.2367	419	0.0491	500	0.2031	**403**	**0.0113**	411	0.0306	411	0.0306	**399**
7	416	0.0524	517	0.2375	415	0.0501	490	0.1955	**399**	**0.0120**	406	0.0290	406	0.0290	**395**
8	426	0.0536	530	0.2393	425	0.0514	502	0.1969	**408**	**0.0119**	415	0.0293	415	0.0290	**404**
12	423	0.0531	527	0.2400	422	0.0509	497	0.1941	**405**	**0.0111**	413	0.0302	413	0.0302	**401**
17	425	0.0517	531	0.2410	425	0.0517	508	0.2066	**407**	**0.0098**	416	0.0312	415	0.0289	**404**

Table 7.B: Summary Result Table for Itemset-8

ItemSet 8(LS:501 Cap:100)	FF		NF		BF		WF		BFD		ABC		MEABC		Best
	#Bin	Waste	#Bin	Waste	#Bin	Waste	#Bin	Waste	#Bin	Waste	#Bin	Waste	#Bin	Waste	#Bin
8	179	0.0670	199	0.1608	179	0.0670	187	0.1070	189	0.1164	**175**	**0.0473**	176	0.0528	**167**
10	178	0.0618	191	0.1257	178	0.0618	183	0.0874	190	0.1211	**175**	**0.0478**	176	0.0511	**167**
13	179	0.0670	204	0.1814	179	0.0670	194	0.1392	190	0.1211	176	0.0529	176	0.0529	**167**
16	180	0.0722	197	0.1523	179	0.0670	186	0.1022	191	0.1257	176	0.0531	**176**	**0.0530**	**167**
19	179	0.0670	202	0.1733	179	0.0670	186	0.1022	189	0.1164	177	0.0565	**176**	**0.0511**	**167**

According to the results of the MEABC algorithm, each approach obtains almost the same solution for all item-sets. Classic ABC algorithm generally beats the approached MEABC algorithm. On the other hand, the MEABC algorithm obtains better results than the classic ABC algorithm as illustrated in Table 11 (Appendix B page 93) for experiment group DS13, in table 12 (Appendix B page 96) for experiment group DS17, and in Table 16 (Appendix B page 124) for experiment group DS19 probably because of experimental run randomness.

In fact, throughout this study, different subsidiary approach techniques with various parameter values were applied to improve the classic ABC algorithm; however, in the 1-D bin packing algorithm, the proposed approach cannot produce significant results to be considered as an improvement.

Possible reasons for this case can be considered as follows:

- It is a fact that the ABC algorithm could be more effective for real number based functions, so the bin packing problem is a branch of integer programming and the main drawback of this method is that there are lots of solutions in the feasible area between two integers and this

method cannot benefit these solutions. In the 1-D bin packing problem, algorithms from literature may not find the actual solution.

- Both algorithms restrict the search by using the counter operator in classic ABC algorithm and tabu period in the proposed MEABC algorithm. These operators may prevent a further search in the feasible area.
- The classic and proposed algorithm might require a higher number of iterations to reach the optimum solution; however, in this case the application of these algorithms can reach a high cost. At least the mentioned algorithm run times should be reasonably short to be considered as a candidate run time because traditional algorithms solve the problem in a very short time.
- The classic ABC algorithm also has its own control parameter unlike in Pham et al.'s bees algorithm. In this case, it is unavoidable that both classic ABC algorithm and proposed MEABC algorithm obtain the same optimum solutions. Although the MEABC algorithm proposes a better memory system, the classic ABC algorithm also has a kind of immature short term memory. According to all the results, it seems that the classic ABC algorithm developed by Karaboga does not require a memory system at least for integer programming.

Chapter 5: Conclusion

In this study, one of the common NP-hard Knapsack problems, the 1-D bin packing problem, is handled to improve the standard results obtained by well-known packing algorithms from literature with new approaches. Deterministic methods do not show sufficient performance for the tackled complex type bin packing problem. In order to fulfil this purpose, one of the heuristic approaches is applied instead of a deterministic approach to overcome the mentioned difficulty.

Recent research about heuristic optimisation has achieved various outcomes such as new approximation methods for complex problems and one of those outcomes is an artificial bee colony (ABC) algorithm based on swarm intelligence, developed by Karaboga in 2005, and applied on several functions and problems. As a result, we are interested in the ABC algorithm based on past studies about it.

In fact, the main purpose of this study is to make an improvement on the classic ABC algorithm. In the first phase of study, traditional bin packing algorithms were investigated and applied on various item-sets. After this phase, the ABC algorithm was applied on the same item-sets to observe the difference between results of swarm based search and results of fixed traditional algorithm searches.

In order to advance the classic ABC algorithm, we investigated its possible drawbacks and deficiencies. There are two salient drawbacks of ABC algorithm which are randomisation and repetition referred in section 3.1.

As a result of this investigation, an enhancement with memory which is based on restriction for repetitive failures by saving them in a list in order to escape from possible local optimums was determined as a starting point for improvement.

In the last phase of the study, the proposed approach which is a modified form of the classic ABC algorithm was applied on the same item-sets to observe the difference. According to the obtained results, the classic ABC algorithm and proposed memory embedded artificial bee colony (MEABC) algorithm can be considered as strong candidates to solve 1-D bin packing problems in comparison with traditional 1-D bin packing algorithms. Both algorithms beat traditional algorithms when they

are applied on triplet sets (itemset-5, 6, 7, 8) however; they cannot show same performance when they are applied on normal distributed sets (itemset-1, 2, 3, 4). Besides, it takes a much longer time to reduce the wastage to the percentage obtained by traditional algorithms. In other words, in order to obtain a better solution than traditional algorithms, we have to tolerate run time.

When we focus on differences between the classic ABC algorithm and proposed MEABC algorithm, memory enhancement cannot differentiate the results of the classic ABC algorithm in an overall outlook. However, a few experiments could be considered as exceptions because of the randomness characteristic explained in previous chapter.

On the other hand, the proposed idea about the ABC algorithm could be applied on various real valued functions rather than integer programming like the tackled problem in this study because generating a new solution for an improvement in the search is restricted by integer values. In case of unrestricted search, the proposed algorithm would be more effective.

In addition, we restricted the search to 7500 iterations which is determined by several trials and we cannot estimate how much iteration is required especially by itemset-4 to obtain an exact solution. It is possible that both classic ABC algorithm and proposed MEABC algorithm may obtain the global optimum but it would also take a very long time and this condition would not be found practical by executors. Saving one more bin by a further search over a long period of time would not be acceptable so, in this case, we also need to optimise the run time.

It is a fact that Pham et al.'s bees algorithm does not involve a control parameter. In this case, the proposed idea can increase the performance of Pham et al.'s bees algorithm. On the other hand, Pham et al. [30] separate bees in onlooker bee phase in order to their performance value and choose bees for next phase from promising and unpromising ones in a rate. This speciality may increase the performance of ABC algorithm in same phase [29]. In fact, these two conditions would be adjunct factors for each ABC and Bees algorithms.

In this study, we focus on memorising the unpromising solutions to avoid hill climbing. According to tabu list idea, proposed algorithm just saves unpromising solutions for a period however, proposed algorithm does not categorise mentioned solutions when applied on classic ABC algorithm. In this case, it is possible that, applied algorithm may generate a huge number of unpromising solutions that not eligible for obtaining global optimum. Instead, we can decrease the number of processed solutions by categorising according to performance quality. On the other hand, decreasing the number of processed solution by using this method may cause a hill climbing easier than randomisation method however; we can solve this problem by using memory system again.

Xiang and An [38] propose a chaotic initialisation method in which initial population in next iteration is subject to current population, to make applied algorithm more robust. Same technique can be applied on ABC algorithm for an alternative improvement. Moreover, chaotic initialisation method can be combined with Pham et al.'s choice system and then a memory system like proposed in this study can be integrated to this combined algorithm. On the other hand, memory idea is able to be applied on each aforementioned algorithm separately.

All these proposals show that, we can reinforce current ABC algorithm and proposed MEABC algorithm with aforementioned beneficial structures of other algorithms for further improvements.

As a result, the proposed idea is promising by having a memory system so; it would be applicable for other algorithms beside Karaboga's ABC algorithm [29]. However, we need to consider the structure of the tackled problem firstly, and then we can determine how to integrate a memory system to chosen applied algorithms.

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Appendix A

Table-1: Results of Traditional 1-D Bin Packing Algorithms for Itemset-1

Data Set (LS:120 Cap:150)	First-Fit		Next-Fit		Best-Fit		Worst-Fit		Best-Fit Decreasing		Best Solution
	#Bin	Waste	#Bin	Waste	#Bin	Waste	#Bin	Waste	#Bin	Waste	#Bin
1	50	0.0563	64	0.2627	51	0.0748	59	0.2002	49	0.037	48
2	51	0.0582	63	0.2376	51	0.0582	61	0.2126	49	0.0197	49
3	48	0.0564	57	0.2054	48	0.0564	57	0.2054	47	0.0363	46
4	52	0.066	65	0.2528	53	0.0836	63	0.2291	50	0.0287	49
5	52	0.0572	64	0.234	52	0.0572	64	0.234	50	0.0195	50
6	52	0.0869	61	0.2216	52	0.0869	58	0.1814	49	0.031	48
7	51	0.0671	63	0.2448	51	0.0671	59	0.1936	49	0.029	48
8	52	0.0647	63	0.228	52	0.0647	60	0.1894	50	0.0273	49
9	54	0.0768	67	0.2559	53	0.0594	65	0.233	51	0.0225	51
10	49	0.0653	61	0.2492	49	0.0653	58	0.2103	47	0.0255	46
11	56	0.0857	68	0.2471	55	0.0691	66	0.2242	52	0.0154	52
12	52	0.0709	63	0.2331	51	0.0527	61	0.208	50	0.0337	49
13	52	0.0795	62	0.228	51	0.0614	60	0.2022	49	0.0231	48
14	51	0.0586	63	0.2379	51	0.0586	60	0.1998	49	0.0201	49
15	53	0.0726	64	0.232	53	0.0726	63	0.2198	50	0.0169	50
16	53	0.1067	63	0.2485	52	0.0895	59	0.1975	49	0.0337	48
17	56	0.0848	69	0.2572	56	0.0848	65	0.2115	52	0.0144	52
18	56	0.083	70	0.2664	56	0.083	67	0.2335	53	0.0311	52
19	52	0.0699	64	0.2443	51	0.0516	61	0.2071	50	0.0327	49
20	52	0.0613	65	0.249	52	0.0613	62	0.2127	50	0.0237	50
MEAN	52.2	0.0714	63.95	0.2418	52	0.0679	61.4	0.2103	49.75	0.0261	49.15
STANDART DEVIATION	1.8482	0.0124	2.5704	0.0118	1.8150	0.0121	2.7508	0.0156	1.3733	0.0062	1.6121

Table-2: Results of Traditional 1-D Bin Packing Algorithms for Itemset-2

Data Set (LS:250 Cap:150)	First-Fit		Next-Fit		Best-Fit		Worst-Fit		Best-Fit Decreasing		Best Solution
	#Bin	Waste	#Bin	Waste	#Bin	Waste	#Bin	Waste	#Bin	Waste	#Bin
1	104	0.0524	131	0.2477	104	0.0524	122	0.1922	100	0.0145	99
2	107	0.0745	129	0.2324	108	0.0831	127	0.2203	101	0.0195	100
3	109	0.0695	133	0.2374	109	0.0695	129	0.2138	104	0.0248	102
4	106	0.062	129	0.2293	106	0.062	124	0.1982	101	0.0156	100
5	107	0.0597	133	0.2435	107	0.0597	128	0.214	102	0.0136	101
6	107	0.0577	132	0.2362	106	0.0488	128	0.2123	104	0.0305	101
7	107	0.0558	132	0.2346	106	0.0469	128	0.2107	103	0.0192	102
8	110	0.0656	139	0.2605	109	0.057	129	0.2032	105	0.0211	104
9	112	0.0633	140	0.2506	111	0.0548	135	0.2229	107	0.0195	105
10	108	0.0722	133	0.2466	108	0.0722	125	0.1984	102	0.0176	101
11	112	0.0681	137	0.2382	112	0.0681	132	0.2093	106	0.0153	105
12	109	0.076	135	0.254	109	0.076	131	0.2312	103	0.0222	101
13	112	0.0632	139	0.2451	111	0.0547	135	0.2228	107	0.0194	106
14	110	0.0731	134	0.2391	108	0.0559	126	0.1908	104	0.0196	103
15	105	0.0556	130	0.2372	105	0.0556	124	0.2003	101	0.0182	100
16	114	0.0806	140	0.2513	113	0.0724	135	0.2236	107	0.0204	105
17	103	0.063	130	0.2576	103	0.063	122	0.2089	99	0.0251	97
18	106	0.0645	129	0.2313	106	0.0645	125	0.2067	101	0.0182	100
19	106	0.0594	131	0.2389	106	0.0594	123	0.1894	102	0.0225	100
20	108	0.0615	133	0.2379	107	0.0527	127	0.2019	103	0.0159	102
MEAN	108.1	0.0649	133.45	0.2425	107.7	0.0614	127.75	0.2085	103.1	0.0196	101.7
STANDART DEVIATION	2.8691	0.0069	3.7096	0.0089	2.6176	0.0081	4.1233	0.0115	2.3256	0.0039	2.3389

Table-3: Results of Traditional 1-D Bin Packing Algorithms for Itemset-3

Data Set (LS:500 Cap:150)	First-Fit		Next-Fit		Best-Fit		Worst-Fit		Best-Fit Decreasing		Best Solution
	#Bin	Waste	#Bin	Waste	#Bin	Waste	#Bin	Waste	#Bin	Waste	#Bin
1	211	0.0636	260	0.2401	211	0.0636	249	0.2065	201	0.017	198
2	213	0.0571	262	0.2334	212	0.0526	252	0.203	204	0.0155	201
3	212	0.0498	265	0.2398	211	0.0453	257	0.2162	205	0.0174	202
4	216	0.0564	270	0.2451	215	0.052	256	0.2039	207	0.0154	204
5	219	0.0634	273	0.2487	218	0.0591	259	0.2081	209	0.0186	206
6	219	0.0635	272	0.246	218	0.0592	262	0.2172	207	0.0092	206
7	220	0.0596	273	0.2422	218	0.051	260	0.2043	210	0.0148	207
8	219	0.0686	269	0.2417	217	0.06	257	0.2063	207	0.0146	204
9	207	0.0547	258	0.2416	207	0.0547	246	0.2046	199	0.0167	196
10	213	0.0561	263	0.2355	212	0.0516	249	0.1925	204	0.0144	202
11	210	0.0521	268	0.2572	209	0.0475	249	0.2005	202	0.0145	200
12	212	0.0593	264	0.2446	210	0.0503	250	0.2023	203	0.0176	200
13	210	0.0542	262	0.2419	210	0.0542	247	0.1959	202	0.0167	199
14	208	0.0597	255	0.233	207	0.0551	243	0.1951	198	0.0122	196
15	215	0.0557	268	0.2424	214	0.0513	254	0.2007	206	0.0144	204
16	212	0.056	263	0.239	212	0.056	249	0.1963	204	0.019	201
17	212	0.0519	268	0.25	211	0.0474	249	0.1927	205	0.0195	202
18	207	0.0462	264	0.2522	207	0.0462	250	0.2103	201	0.0178	198
19	212	0.0505	264	0.2375	213	0.055	249	0.1916	205	0.0181	202
20	208	0.0595	259	0.2447	207	0.0549	242	0.1916	199	0.0169	196
MEAN	212.75	0.0569	265	0.2428	211.95	0.0534	251.45	0.2020	203.9	0.0160	201.2
STANDART DEVIATION	4.2962	0.0053	5.1246	0.0059	3.9478	0.0040	5.6522	0.0071	3.4129	0.0026	3.4633

Table-4: Results of Traditional 1-D Bin Packing Algorithms for Itemset-4

Data Set (LS:1000 Cap:150)	First-Fit		Next-Fit		Best-Fit		Worst-Fit		Best-Fit Decreasing		Best Solution
	#Bin	Waste	#Bin	Waste	#Bin	Waste	#Bin	Waste	#Bin	Waste	#Bin
1	420	0.0514	522	0.2367	419	0.0491	500	0.2031	403	0.0113	399
2	427	0.0509	534	0.2411	426	0.0487	512	0.2085	411	0.014	406
3	433	0.0527	545	0.2473	432	0.0505	520	0.2112	416	0.0139	411
4	435	0.0555	542	0.2419	434	0.0533	517	0.2053	416	0.0123	411
5	419	0.0531	521	0.2385	418	0.0509	495	0.1985	402	0.0131	397
6	421	0.0535	532	0.251	419	0.0489	498	0.1998	404	0.0136	399
7	416	0.0524	517	0.2375	415	0.0501	490	0.1955	399	0.012	395
8	426	0.0536	530	0.2393	425	0.0514	502	0.1969	408	0.0119	404
9	419	0.0491	531	0.2497	418	0.0468	498	0.1999	404	0.0138	399
10	418	0.0504	523	0.2411	419	0.0527	490	0.1899	404	0.0175	397
11	420	0.0492	528	0.2437	419	0.0469	498	0.1981	404	0.0115	400
12	423	0.0531	527	0.24	422	0.0509	497	0.1941	405	0.0111	401
13	414	0.0526	519	0.2442	411	0.0456	483	0.1879	398	0.0145	393
14	415	0.0475	517	0.2354	414	0.0452	491	0.195	401	0.0143	396
15	415	0.0509	517	0.2381	414	0.0486	492	0.1994	400	0.0153	394
16	422	0.0479	530	0.2419	423	0.0501	506	0.2059	408	0.0152	402
17	425	0.0517	531	0.241	425	0.0517	508	0.2066	407	0.0098	404
18	422	0.0431	535	0.2452	423	0.0454	507	0.2036	409	0.0127	404
19	419	0.0497	526	0.243	419	0.0497	498	0.2004	403	0.0119	399
20	421	0.0515	521	0.2335	419	0.0469	495	0.1933	406	0.0164	400
MEAN	421.5	0.0510	527.4	0.2415	420.7	0.0492	499.85	0.1996	405.4	0.0133	400.55
STANDART DEVIATION	4.9044	0.0029	6.9056	0.0044	5.1973	0.0025	7.9793	0.0052	4.2060	0.0020	4.3400

Table-5: Results of Traditional 1-D Bin Packing Algorithms for Itemset-5

Data Set (LS:60 Cap:100)	First-Fit		Next-Fit		Best-Fit		Worst-Fit		Best-Fit Decreasing		Best Solution
	#Bin	Waste	#Bin	Waste	#Bin	Waste	#Bin	Waste	#Bin	Waste	#Bin
1	22	0.0909	24	0.1667	22	0.0909	23	0.1304	23	0.1304	20
2	21	0.0476	21	0.0476	21	0.0476	21	0.0476	23	0.1304	20
3	22	0.0909	23	0.1304	22	0.0909	22	0.0909	23	0.1304	20
4	23	0.1304	25	0.2	23	0.1304	24	0.1667	23	0.1304	20
5	21	0.0476	25	0.2	21	0.0476	22	0.0909	24	0.1667	20
6	22	0.0909	24	0.1667	22	0.0909	23	0.1304	23	0.1304	20
7	22	0.0909	22	0.0909	22	0.0909	21	0.0476	23	0.1304	20
8	21	0.0476	23	0.1304	21	0.0476	22	0.0909	23	0.1304	20
9	22	0.0909	24	0.1667	22	0.0909	23	0.1304	23	0.1304	20
10	22	0.0909	24	0.1667	22	0.0909	23	0.1304	23	0.1304	20
11	22	0.0909	24	0.1667	22	0.0909	23	0.1304	23	0.1304	20
12	23	0.1304	25	0.2	23	0.1304	23	0.1304	24	0.1667	20
13	22	0.0909	22	0.0909	22	0.0909	21	0.0476	23	0.1304	20
14	22	0.0909	23	0.1304	22	0.0909	22	0.0909	23	0.1304	20
15	22	0.0909	24	0.1667	22	0.0909	23	0.1304	23	0.1304	20
16	22	0.0909	24	0.1667	22	0.0909	23	0.1304	23	0.1304	20
17	21	0.0476	23	0.1304	21	0.0476	22	0.0909	24	0.1667	20
18	22	0.0909	24	0.1667	22	0.0909	24	0.1667	24	0.1667	20
19	22	0.0909	24	0.1667	22	0.0909	23	0.1304	23	0.1304	20
20	22	0.0909	23	0.1304	22	0.0909	22	0.0909	23	0.1304	20
MEAN	21.9	0.0862	23.55	0.1491	21.9	0.0862	22.5	0.1098	23.2	0.1377	20
STANDART DEVIATION	0.5392	0.0225	0.8929	0.0324	0.5392	0.0225	0.8445	0.0336	0.4243	0.0154	0.0000

Table-6: Results of Traditional 1-D Bin Packing Algorithms for Itemset-6

Data Set (LS:120 Cap:100)	First-Fit		Next-Fit		Best-Fit		Worst-Fit		Best-Fit Decreasing		Best Solution
	#Bin	Waste	#Bin	Waste	#Bin	Waste	#Bin	Waste	#Bin	Waste	#Bin
1	43	0.0698	47	0.1489	43	0.0698	46	0.1304	45	0.1111	40
2	43	0.0698	47	0.1489	43	0.0698	45	0.1111	45	0.1111	40
3	42	0.0476	47	0.1489	42	0.0476	44	0.0909	45	0.1111	40
4	44	0.0909	48	0.1667	44	0.0909	45	0.1111	46	0.1304	40
5	44	0.0909	47	0.1489	44	0.0909	45	0.1111	46	0.1304	40
6	44	0.0909	46	0.1304	44	0.0909	44	0.0909	46	0.1304	40
7	43	0.0698	46	0.1304	43	0.0698	44	0.0909	45	0.1111	40
8	43	0.0698	48	0.1667	43	0.0698	46	0.1304	46	0.1304	40
9	43	0.0698	48	0.1667	43	0.0698	45	0.1111	46	0.1304	40
10	43	0.0698	49	0.1837	43	0.0698	45	0.1111	45	0.1111	40
11	44	0.0909	48	0.1667	44	0.0909	46	0.1304	46	0.1304	40
12	43	0.0698	49	0.1837	43	0.0698	47	0.1489	46	0.1304	40
13	43	0.0698	47	0.1489	43	0.0698	45	0.1111	46	0.1304	40
14	44	0.0909	47	0.1489	43	0.0698	44	0.0909	46	0.1304	40
15	43	0.0698	46	0.1304	43	0.0698	43	0.0698	46	0.1304	40
16	44	0.0909	47	0.1489	44	0.0909	45	0.1111	46	0.1304	40
17	43	0.0698	46	0.1304	43	0.0698	45	0.1111	46	0.1304	40
18	43	0.0698	46	0.1304	43	0.0698	44	0.0909	47	0.1489	40
19	43	0.0698	45	0.1111	43	0.0698	44	0.0909	46	0.1304	40
20	44	0.0909	49	0.1837	44	0.0909	47	0.1489	46	0.1304	40
MEAN	43.3	0.0761	47.15	0.1512	43.25	0.0750	44.95	0.1097	45.8	0.1265	40
STANDART DEVIATION	0.4929	0.0104	1.1998	0.0216	0.4785	0.0101	1.0556	0.0207	0.4173	0.0079	0.0000

Table-7: Results of Traditional 1-D Bin Packing Algorithms for Itemset-7

Data Set (LS:249 Cap:100)	First-Fit		Next-Fit		Best-Fit		Worst-Fit		Best-Fit Decreasing		Best Solution
	#Bin	Waste	#Bin	Waste	#Bin	Waste	#Bin	Waste	#Bin	Waste	#Bin
1	89	0.0674	98	0.1531	89	0.0674	93	0.1075	94	0.117	83
2	89	0.0674	98	0.1531	89	0.0674	93	0.1075	95	0.1263	83
3	88	0.0568	98	0.1531	88	0.0568	92	0.0978	94	0.117	83
4	89	0.0674	97	0.1443	89	0.0674	92	0.0978	95	0.1263	83
5	90	0.0778	98	0.1531	90	0.0778	93	0.1075	95	0.1263	83
6	89	0.0674	94	0.117	89	0.0674	91	0.0879	95	0.1263	83
7	91	0.0879	97	0.1443	91	0.0879	93	0.1075	95	0.1263	83
8	89	0.0674	100	0.17	89	0.0674	92	0.0978	96	0.1354	83
9	88	0.0568	98	0.1531	88	0.0568	92	0.0978	95	0.1263	83
10	88	0.0568	95	0.1263	88	0.0568	90	0.0778	95	0.1263	83
11	89	0.0674	100	0.17	89	0.0674	92	0.0978	95	0.1263	83
12	89	0.0674	97	0.1443	89	0.0674	92	0.0978	96	0.1354	83
13	88	0.0568	101	0.1782	89	0.0674	94	0.117	94	0.117	83
14	90	0.0778	99	0.1616	90	0.0778	92	0.0978	96	0.1354	83
15	89	0.0674	97	0.1443	89	0.0674	91	0.0879	95	0.1263	83
16	89	0.0674	99	0.1616	89	0.0674	93	0.1075	95	0.1263	83
17	90	0.0778	101	0.1782	90	0.0778	94	0.117	96	0.1354	83
18	89	0.0674	100	0.17	89	0.0674	93	0.1075	94	0.117	83
19	90	0.0778	99	0.1616	90	0.0778	94	0.117	94	0.117	83
20	90	0.0778	98	0.1531	90	0.0778	94	0.117	96	0.1354	83
MEAN	89.15	0.0689	98.2	0.1545	89.2	0.0694	92.5	0.1026	95	0.1263	83
STANDART DEVIATION	0.8068	0.0084	1.8952	0.0165	0.7490	0.0078	1.1437	0.0111	0.6764	0.0062	0.0000

Table-8: Results of Traditional 1-D Bin Packing Algorithms for Itemset-8

Data Set (LS:501 Cap:100)	First-Fit		Next-Fit		Best-Fit		Worst-Fit		Best-Fit Decreasing		Best Solution
	#Bin	Waste	#Bin	Waste	#Bin	Waste	#Bin	Waste	#Bin	Waste	#Bin
1	178	0.0618	196	0.148	178	0.0618	184	0.0924	190	0.1211	167
2	181	0.0773	200	0.165	180	0.0722	186	0.1022	191	0.1257	167
3	178	0.0618	194	0.1392	178	0.0618	186	0.1022	190	0.1211	167
4	178	0.0618	196	0.148	178	0.0618	188	0.1117	191	0.1257	167
5	178	0.0618	194	0.1392	179	0.067	185	0.0973	191	0.1257	167
6	178	0.0618	194	0.1392	178	0.0618	182	0.0824	190	0.1211	167
7	178	0.0618	197	0.1523	178	0.0618	185	0.0973	190	0.1211	167
8	179	0.067	199	0.1608	179	0.067	187	0.107	189	0.1164	167
9	178	0.0618	199	0.1608	178	0.0618	190	0.1211	191	0.1257	167
10	178	0.0618	191	0.1257	178	0.0618	183	0.0874	190	0.1211	167
11	179	0.067	192	0.1302	179	0.067	184	0.0924	190	0.1211	167
12	177	0.0565	196	0.148	177	0.0565	184	0.0924	190	0.1211	167
13	179	0.067	204	0.1814	179	0.067	194	0.1392	190	0.1211	167
14	179	0.067	195	0.1436	179	0.067	183	0.0874	190	0.1211	167
15	180	0.0722	195	0.1436	179	0.067	184	0.0924	189	0.1164	167
16	180	0.0722	197	0.1523	179	0.067	186	0.1022	191	0.1257	167
17	178	0.0618	198	0.1566	178	0.0618	189	0.1164	189	0.1164	167
18	180	0.0722	200	0.165	179	0.067	187	0.107	191	0.1257	167
19	179	0.067	202	0.1733	179	0.067	186	0.1022	189	0.1164	167
20	178	0.0618	197	0.1523	178	0.0618	185	0.0973	191	0.1257	167
MEAN	178.65	0.0652	196.8	0.1512	178.5	0.0644	185.9	0.1015	190.15	0.1218	167
STANDART DEVIATION	0.8444	0.0044	3.2582	0.0140	0.6057	0.0032	2.9105	0.0138	0.7579	0.0035	0.0000

Appendix B

Table 9.A: Results of Classic ABC Algorithm for Itemset-1 Group-1

Swarm:100 Iteration:7500 Max Number of Fail:100 Minimum Bin Usage Ratio:0.50 Group:1 Optimum Number of Bin:48																		
Test	1		2		3		4		5		OVERALL							
Time(sc)	939.0273		936.5731		936.2996		935.5605		934.8444		BIN				WASTE			
	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Best	No.Best	Mean	St. Dev.	Best	No.Best	Mean	St. Dev.
Best	49	0.037	48	0.0228	48	0.0226	48	0.0226	48	0.0222	48	4	48.2	0.4472	0.0222	1	0.0254	0.0065
Mean	49.038	0.0378	48.981	0.0372	48.949	0.0367	48.511	0.0326	48.962	0.0368	48.511	1	48.888	0.2137	0.0326	1	0.0362	0.0021
St. Dev.	0.3575	0.0067	0.4581	0.0079	0.4625	0.0079	0.6929	0.01	0.4721	0.0081	0.3575	1	0.4886	0.1233	0.0067	1	0.0081	0.0012

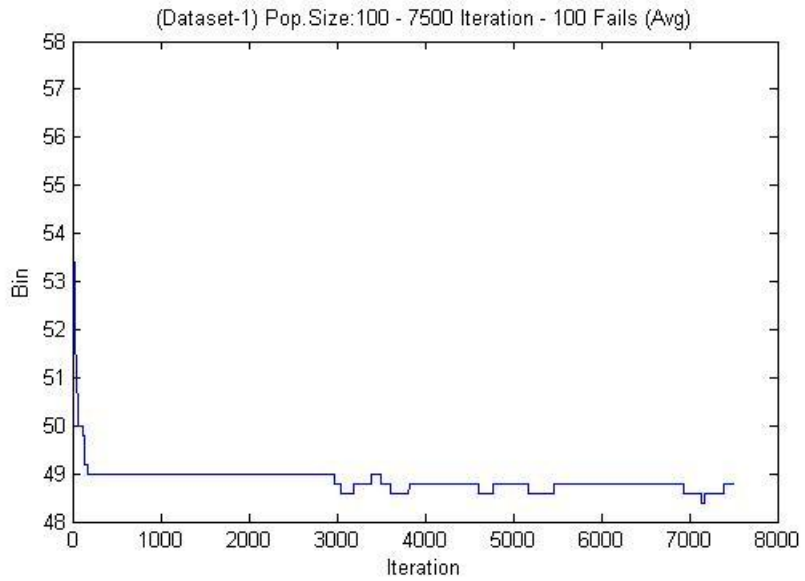

Fig. 1.A: Average Number of Bin for Table 9.A

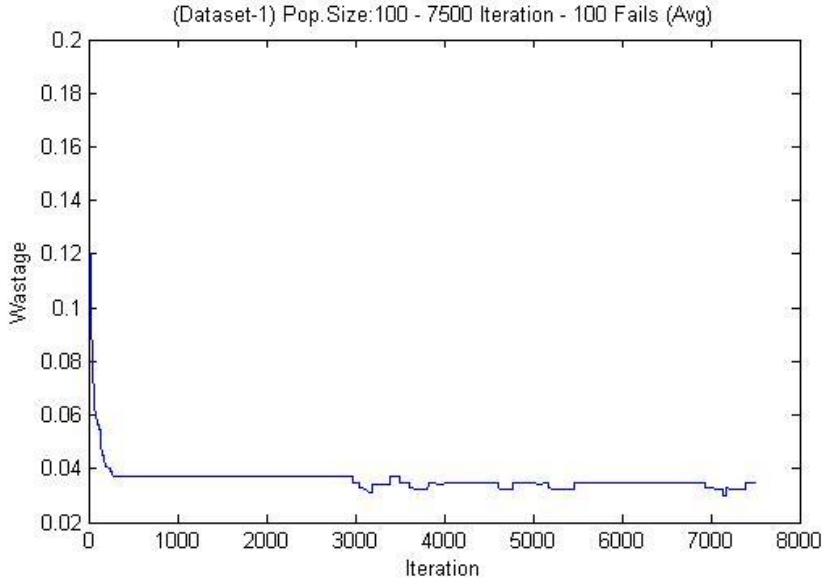

Fig. 1.B: Average Wastage for Table 9.A

Table 9.B: Results of Classic ABC Algorithm for Itemset-1 Group-7

Swarm:100 Iteration:7500 Max Number of Fail:100 Minimum Bin Usage Ratio:0.50 Group:7 Optimum Number of Bin:48																		
Test	1		2		3		4		5		OVERALL							
Time(sc)	997.6559		986.0989		975.8165		981.1598		985.1547		BIN				WASTE			
	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Best	No.Best	Mean	St. Dev.	Best	No.Best	Mean	St. Dev.
Best	49	0.029	49	0.029	49	0.029	49	0.029	49	0.029	49	5	49	0.0000	0.0290	5	0.0290	0.0000
Mean	49.047	0.0301	49.049	0.0303	49.038	0.0298	49.037	0.0301	49.046	0.0298	49.037	1	49.043	0.0057	0.0298	2	0.0300	0.0002
St. Dev.	0.4161	0.0079	0.3926	0.0075	0.3905	0.0073	0.3926	0.0075	0.3926	0.0075	0.3905	1	0.3969	0.0108	0.0073	1	0.0075	0.0002

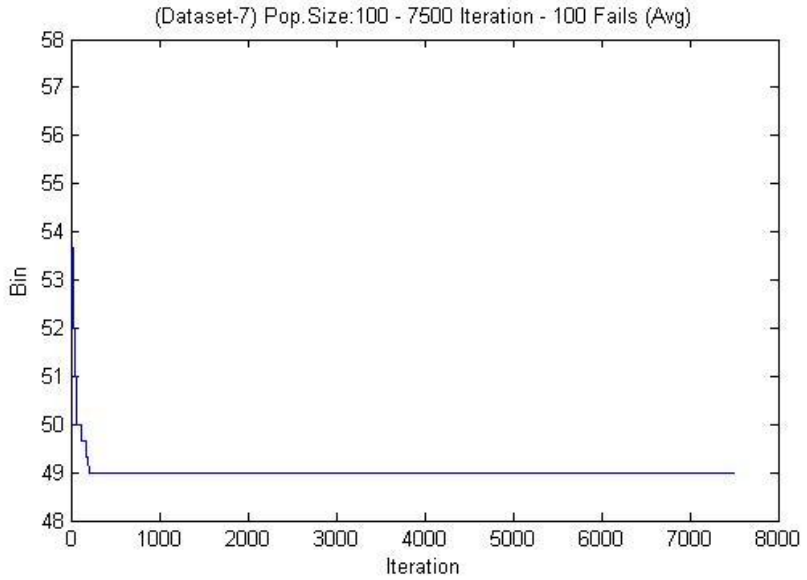

Fig. 2.A: Average Number of Bin for Table 9.B

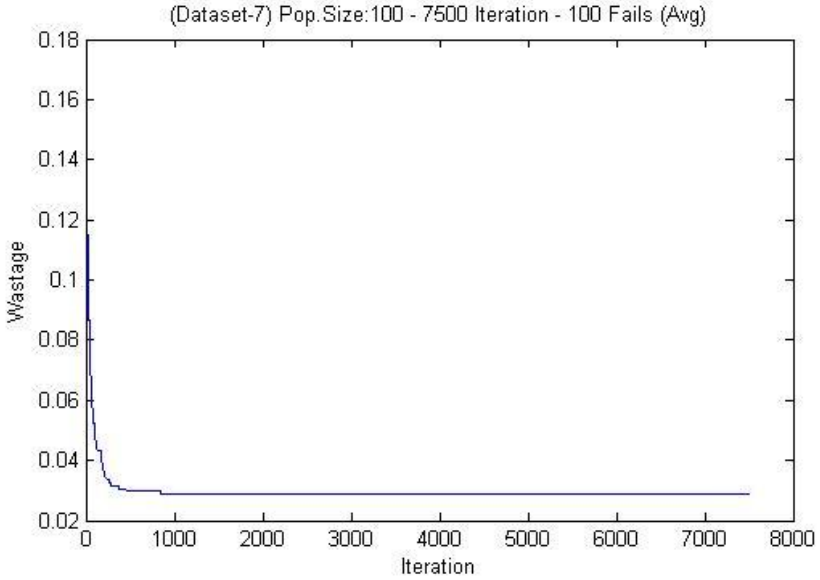

Fig. 2.B: Average Wastage for Table 9.B

Table 9.C: Results of Classic ABC Algorithm for Itemset-1 Group-8

Swarm:100 Iteration:7500 Max Number of Fail:100 Minimum Bin Usage Ratio:0.50 Group:8 Optimum Number of Bin:49																		
Test	1		2		3		4		5		OVERALL							
Time(sc)	1.01E+03		9.91E+02		9.76E+02		9.68E+02		9.86E+02		BIN				WASTE			
	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Best	No.Best	Mean	St. Dev.	Best	No.Best	Mean	St. Dev.
Best	50	0.0273	50	0.0273	50	0.0273	50	0.0273	50	0.0273	50	5	50	0.0000	0.0273	5	0.0273	0.0000
Mean	50.056	0.0295	50.044	0.0285	50.043	0.029	50.044	0.0285	50.056	0.0295	50.043	1	50.048	0.0066	0.0285	2	0.0290	0.0005
St. Dev.	0.3756	0.0071	0.3523	0.0066	0.365	0.007	0.3523	0.0066	0.3756	0.0071	0.3523	2	0.3642	0.0117	0.0066	2	0.0069	0.0003

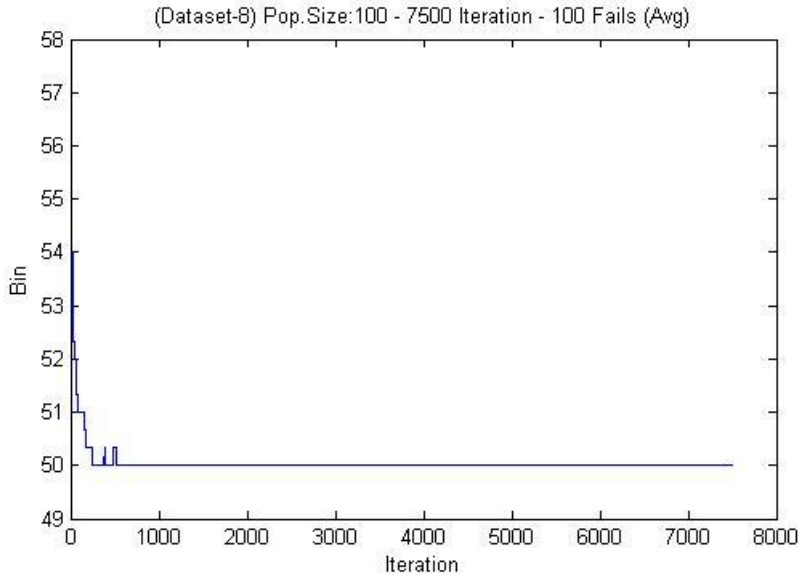

Fig. 3.A: Average Number of Bin for Table 9.C

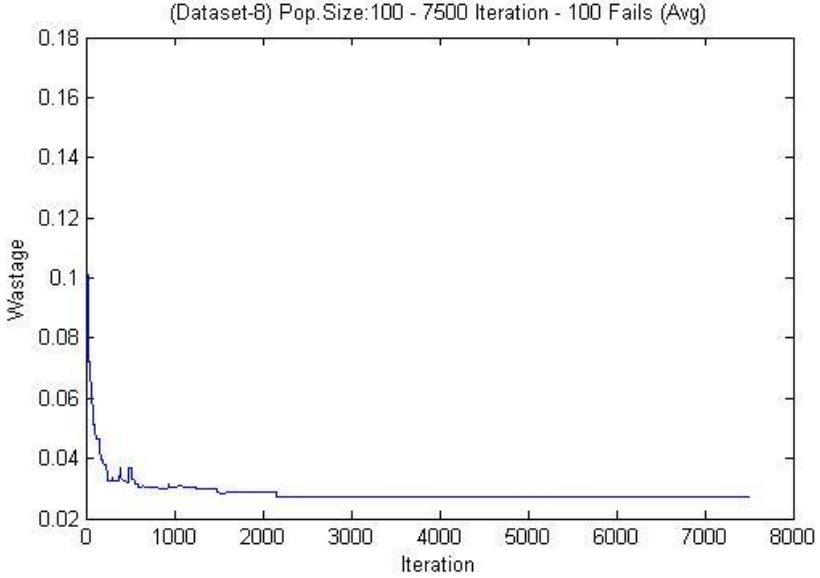

Fig. 3.B: Average Wastage for Table 9.C

Table 9.D: Results of Classic ABC Algorithm for Itemset-1 Group-12

Swarm:100 Iteration:7500 Max Number of Fail:100 Minimum Bin Usage Ratio:0.50 Group:12 Optimum Number of Bin:49																		
Test	1		2		3		4		5		OVERALL							
Time(sc)	965.2107		959.0011		950.5929		978.3648		954.8614		BIN				WASTE			
	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Best	No.Best	Mean	St. Dev.	Best	No.Best	Mean	St. Dev.
Best	50	0.0337	50	0.0337	50	0.0337	50	0.0337	50	0.0337	50	5	50	0.0000	0.0337	5	0.0337	0.0000
Mean	50.050	0.0348	50.060	0.0349	50.062	0.0351	50.050	0.0350	50.050	0.0348	50.050	3	50.054	0.0058	0.0348	2	0.0349	0.0001
St. Dev.	0.4140	0.0078	0.4791	0.0086	0.4693	0.0084	0.4140	0.0078	0.4140	0.0078	0.4140	3	0.4381	0.0332	0.0078	3	0.0081	0.0004

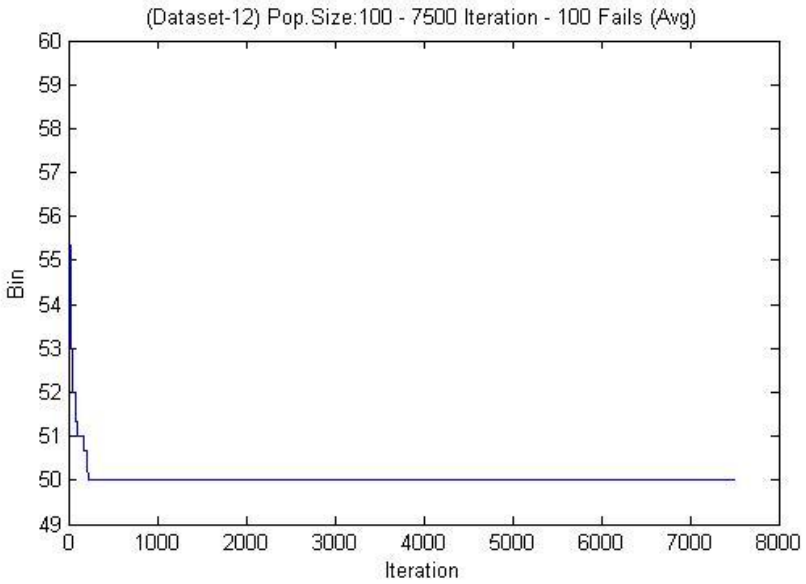

Fig. 4.A: Average Number of Bin for Table 9.D

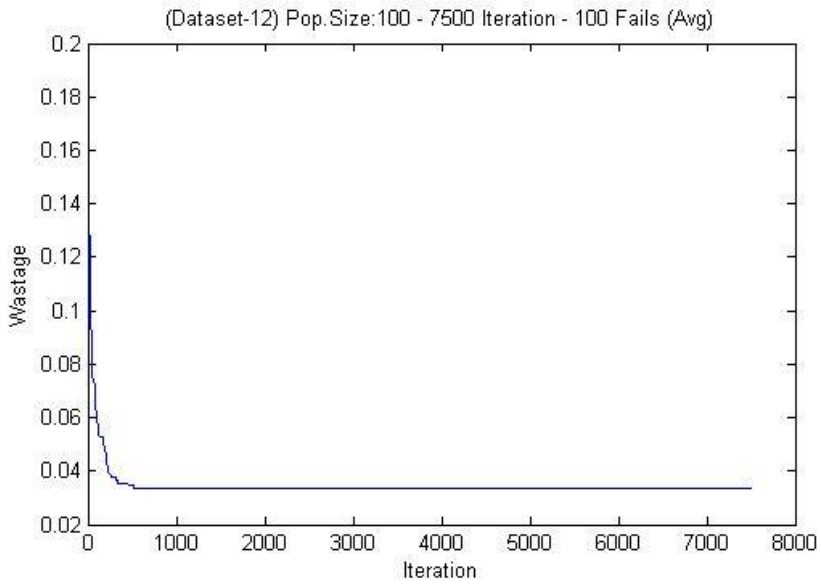

Fig. 4.B: Average Wastage for Table 9.D

Table 9.E: Results of Classic ABC Algorithm for Itemset-1 Group-17

Swarm:100 Iteration:7500 Max Number of Fail:100 Minimum Bin Usage Ratio:0.50 Group:17 Optimum Number of Bin:52																		
Test	1		2		3		4		5		OVERALL							
Time(sc)	999.6798		988.5619		976.8857		971.2657		994.3791		BIN				WASTE			
	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Best	No.Best	Mean	St. Dev.	Best	No.Best	Mean	St. Dev.
Best	53	0.0330	53	0.0330	52	0.0187	53	0.0330	53	0.0330	52	1	52.8	0.4472	0.0187	1	0.0301	0.0064
Mean	53.048	0.0339	53.061	0.0341	52.969	0.0330	53.058	0.0336	53.048	0.0339	52.969	1	53.037	0.0382	0.0330	1	0.0337	0.0004
St. Dev.	0.4690	0.0080	0.5025	0.0085	0.5824	0.0091	0.5025	0.0085	0.4690	0.0080	0.4690	2	0.5051	0.0464	0.0080	2	0.0084	0.0005

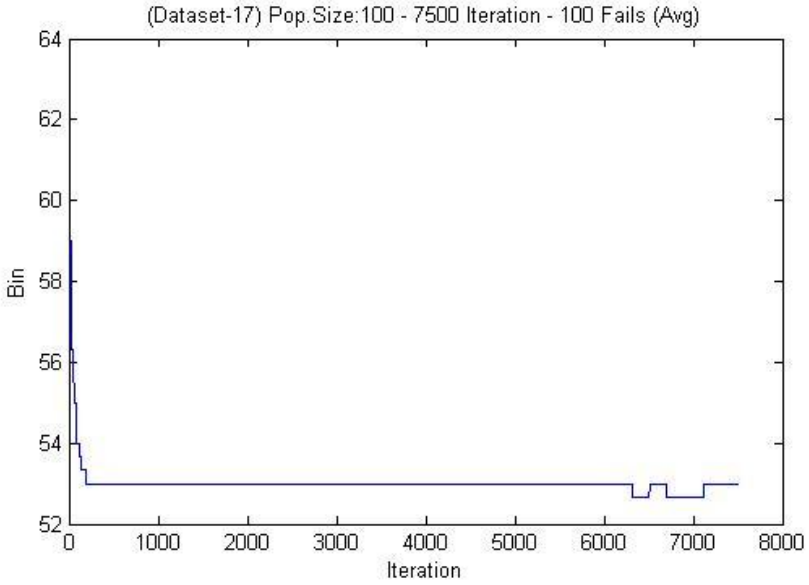

Fig. 5.A: Average Number of Bin for Table 9.E

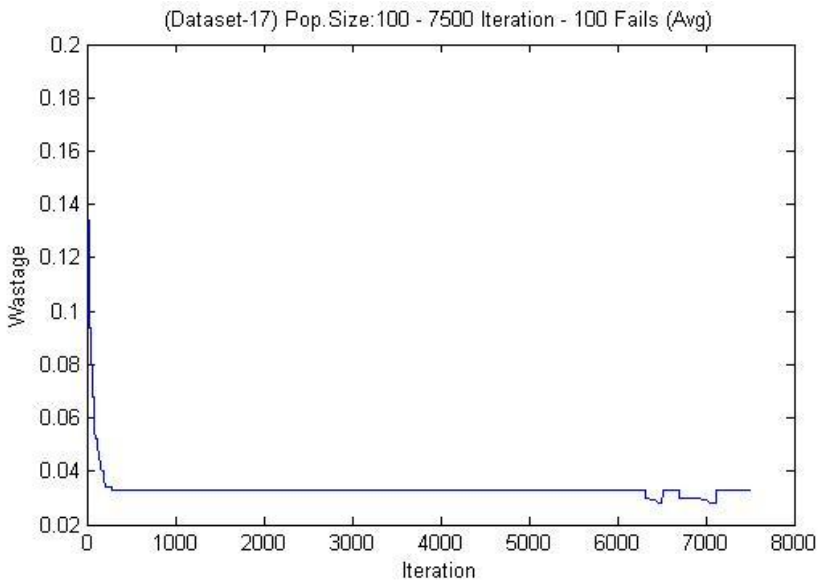

Fig. 5.B: Average Wastage for Table 9.E

Table 10.A: Results of Classic ABC Algorithm for Itemset-2 Group-5

Swarm:100 Iteration:7500 Max Number of Fail:100 Minimum Bin Usage Ratio:0.50 Group:5 Optimum Number of Bin:101																		
Test	1		2		3		4		5		OVERALL							
Time(sc)	2.20E+03		2.20E+03		2.15E+03		2.27E+03		2.13E+03		BIN				WASTE			
	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Best	No.Best	Mean	St. Dev.	Best	No.Best	Mean	St. Dev.
Best	103	0.0256	103	0.0249	103	0.0256	103	0.0256	103	0.0256	103	5	103	0.0000	0.0249	1	0.0255	0.0003
Mean	103.35	0.0329	103.33	0.0327	103.35	0.0329	103.35	0.0329	103.35	0.0329	103.33	1	103.35	0.0089	0.0327	1	0.0329	0.0001
St. Dev.	0.5416	0.0053	0.4136	0.0041	0.5416	0.0053	0.5416	0.0053	0.5416	0.0053	0.4136	1	0.5160	0.0572	0.0041	1	0.0051	0.0005

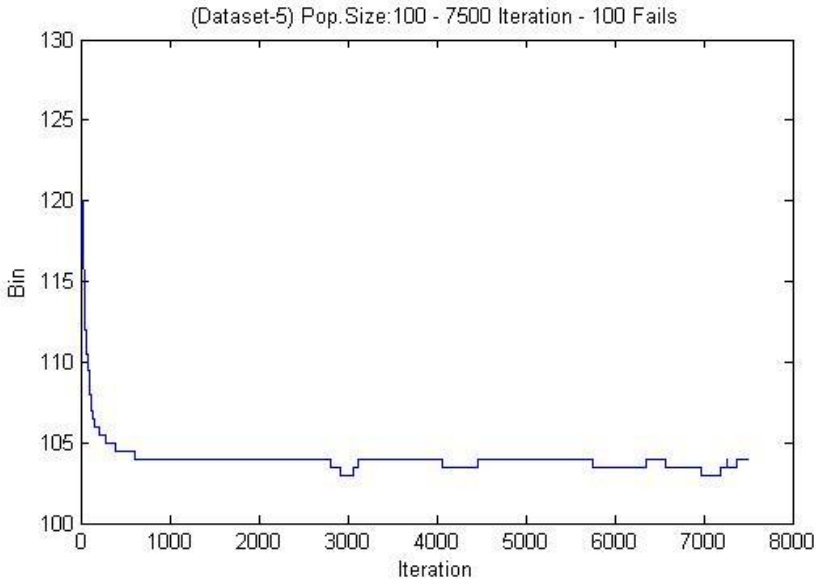

Fig. 6.A: Average Number of Bin for Table 10.A

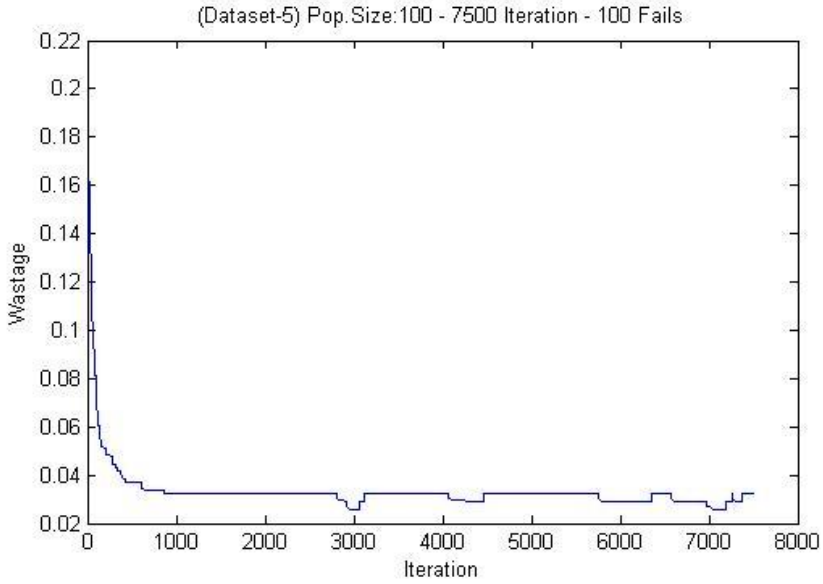

Fig. 6.B: Average Wastage for Table 10.A

Table 10.B: Results of Classic ABC Algorithm for Itemset-2 Group-6

Swarm:100 Iteration:7500 Max Number of Fail:100 Minimum Bin Usage Ratio:0.50 Group:6 Optimum Number of Bin:101																			
Test	1		2		3		4		5		OVERALL								
Time(sc)	2.21E+03		2.34E+03		2.13E+03		2.15E+03		2.29E+03		BIN				WASTE				
	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Best	No.Best	Mean	St. Dev.	Best	No.Best	Mean	St. Dev.	
Best	104	0.0305	104	0.0305	104	0.0305	104	0.0305	104	0.0305	104	5	104	0.0000	0.0305	5	0.0305	0.0000	
Mean	104.39	0.0341	104.33	0.0336	104.36	0.0341	104.38	0.0321	104.37	0.0345	104.327	1	104.364	0.0244	0.0321	1	0.0337	0.0009	
St. Dev.	1.5112	0.0128	1.4908	0.0126	1.5112	0.0128	1.5112	0.0128	1.5112	0.0128	1.4908	1	1.5071	0.0091	0.0126	1	0.0128	0.0001	

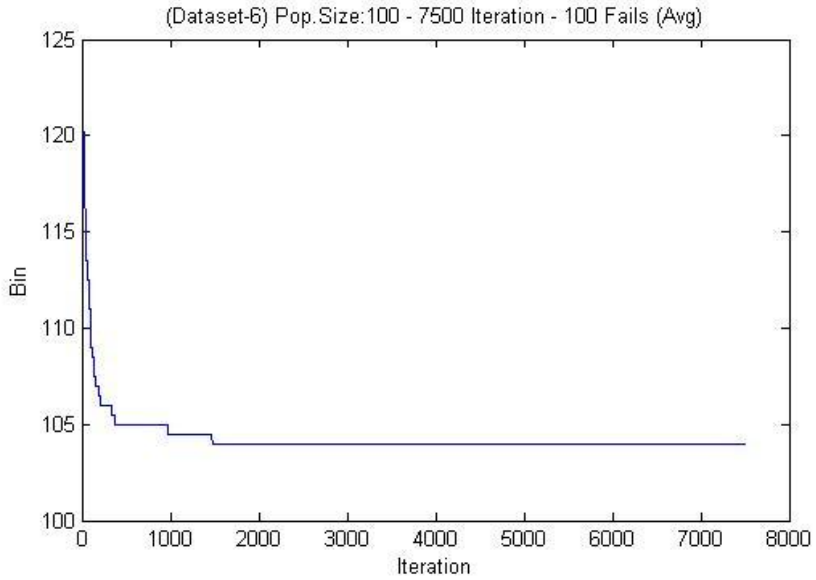

Fig. 7.A: Average Number of Bin for Table 10.B

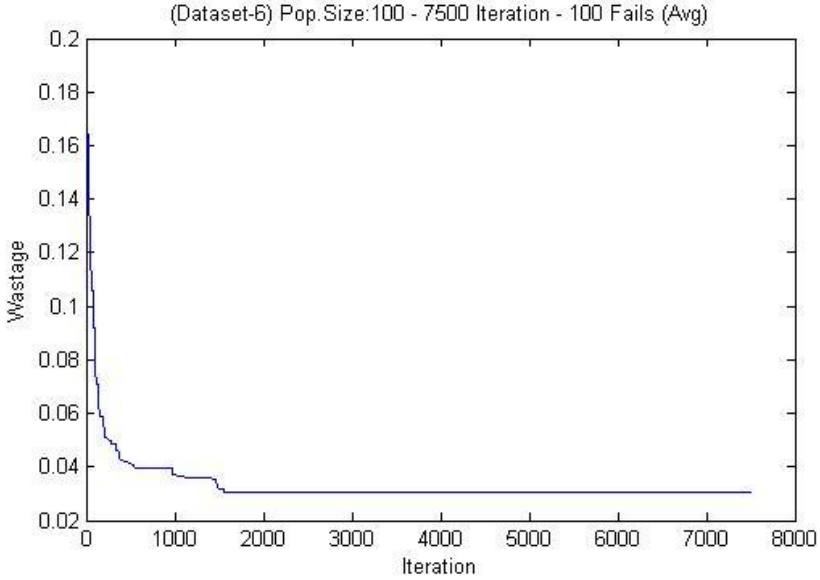

Fig. 7.B: Average Wastage for Table 10.B

Table 10.C: Results of Classic ABC Algorithm for Itemset-2 Group-14

Swarm:100 Iteration:7500 Max Number of Fail:100 Minimum Bin Usage Ratio:0.50 Group:14 Optimum Number of Bin:103																		
Test	1		2		3		4		5		OVERALL							
Time(sc)	2.15E+03		2.35E+03		2.17E+03		2.13E+03		2.25E+03		BIN				WASTE			
	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Best	No.Best	Mean	St. Dev.	Best	No.Best	Mean	St. Dev.
Best	105	0.029	105	0.029	105	0.029	105	0.029	105	0.029	105	5	105	0.0000	0.0290	5	0.0290	0.0000
Mean	105.44	0.0334	105.69	0.0358	105.54	0.0355	105.62	0.0349	105.69	0.0358	105.440	1	105.598	0.1077	0.0334	1	0.0351	0.0010
St. Dev.	1.5267	0.0127	1.4459	0.012	1.4459	0.012	1.4459	0.012	1.4459	0.012	1.4459	4	1.4621	0.0361	0.0120	4	0.0121	0.0003

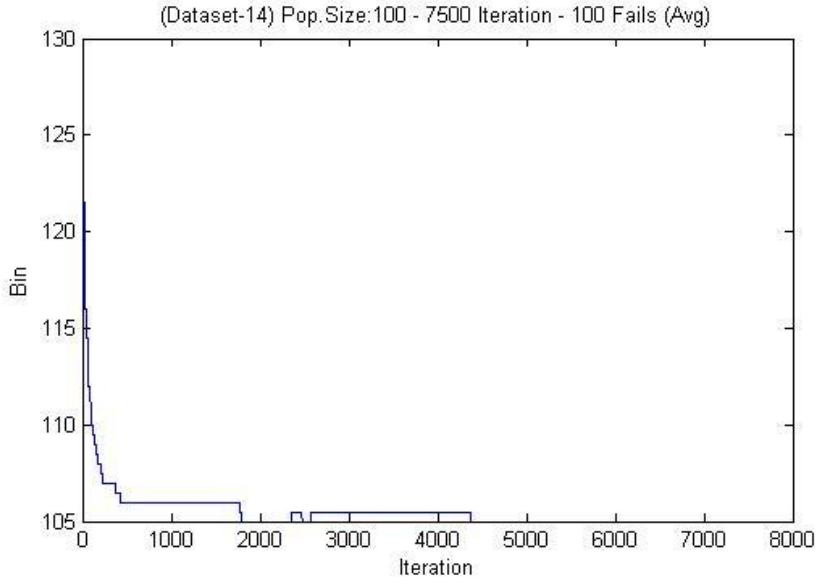

Fig. 8.A: Average Number of Bin for Table 10.B

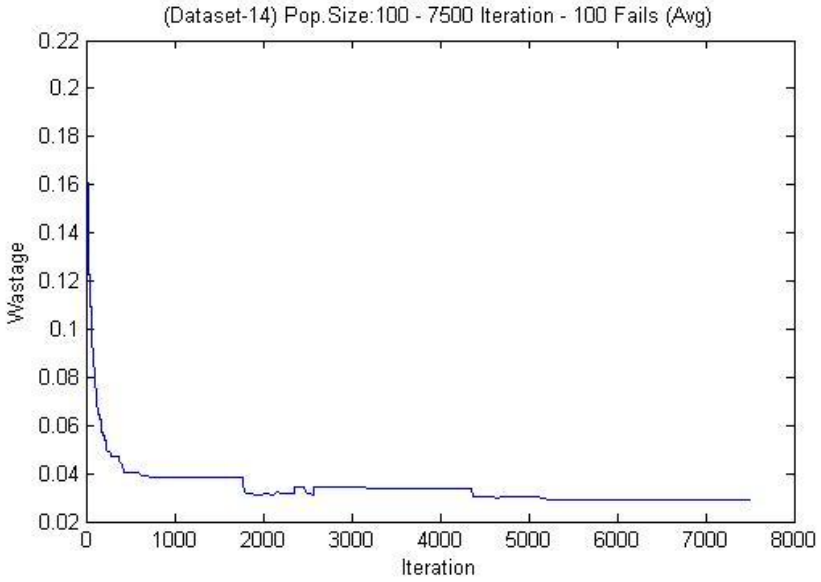

Fig. 8.B: Average Wastage for Table 10.B

Table 10.D: Results of Classic ABC Algorithm for Itemset-2 Group-16

Swarm:100 Iteration:7500 Max Number of Fail:100 Minimum Bin Usage Ratio:0.50 Group:16 Optimum Number of Bin:105																		
Test	1		2		3		4		5		OVERALL							
Time(sc)	2.12E+03		2.12E+03		2.32E+03		2.15E+03		2.13E+03		BIN				WASTE			
	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Best	No.Best	Mean	St. Dev.	Best	No.Best	Mean	St. Dev.
Best	108	0.0295	108	0.0295	108	0.0295	108	0.0295	108	0.0295	108	5	108	0.0000	0.0295	5	0.0295	0.0000
Mean	108.31	0.0323	108.34	0.0326	108.31	0.0323	108.33	0.0326	108.32	0.0326	108.306	2	108.321	0.0163	0.0323	2	0.0325	0.0002
St. Dev.	1.6077	0.0131	1.7157	0.0138	1.6077	0.0131	1.7157	0.0138	1.7157	0.0138	1.6077	2	1.6725	0.0591	0.0131	2	0.0135	0.0004

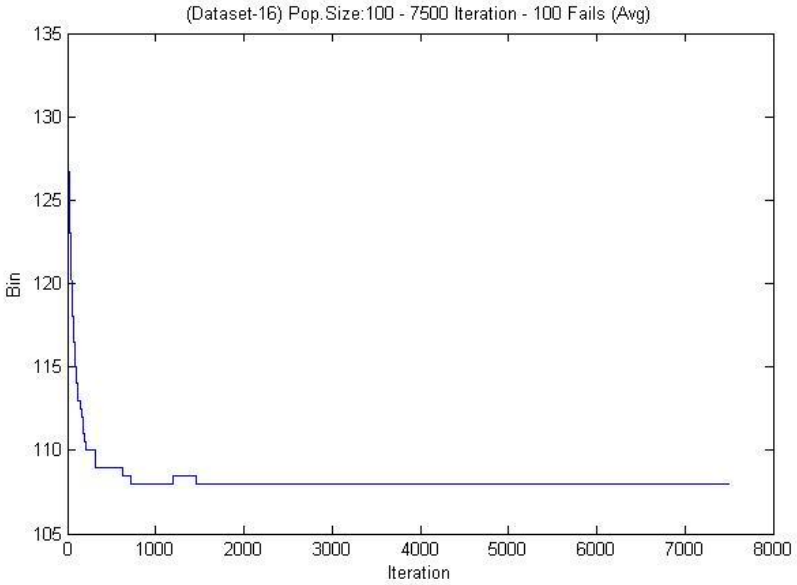

Fig. 9.A: Average Number of Bin for Table 10.D

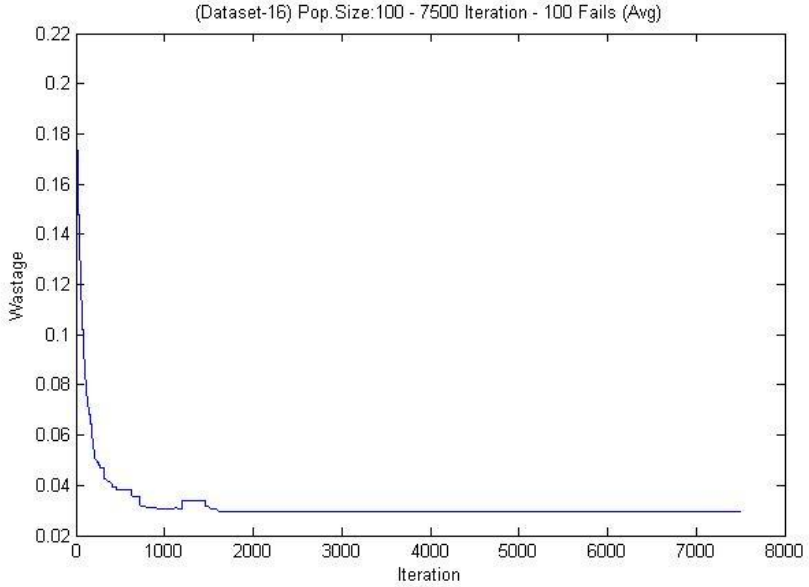

Fig. 9.B: Average Wastage for Table 10.D

Table 10.E: Results of Classic ABC Algorithm for Itemset-2 Group-19

Swarm:100 Iteration:7500 Max Number of Fail:100 Minimum Bin Usage Ratio:0.50 Group:19 Optimum Number of Bin:100																		
Test	1		2		3		4		5		OVERALL							
Time(sc)	2.40E+03		2.40E+03		2.40E+03		2.39E+03		2.40E+03		BIN				WASTE			
	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Best	No.Best	Mean	St. Dev.	Best	No.Best	Mean	St. Dev.
Best	102	0.0239	102	0.0244	102	0.0239	102	0.0241	102	0.0244	102	5	102	0.0000	0.0239	2	0.0241	0.0003
Mean	103.14	0.0337	102.95	0.0324	103.14	0.0337	102.95	0.0345	102.95	0.0324	102.949	2	103.025	0.1034	0.0324	2	0.0333	0.0009
St. Dev.	1.4668	0.0127	0.7272	0.0067	1.4668	0.0127	0.7285	0.0087	0.7272	0.0067	0.7272	2	1.0233	0.4049	0.0067	2	0.0095	0.0030

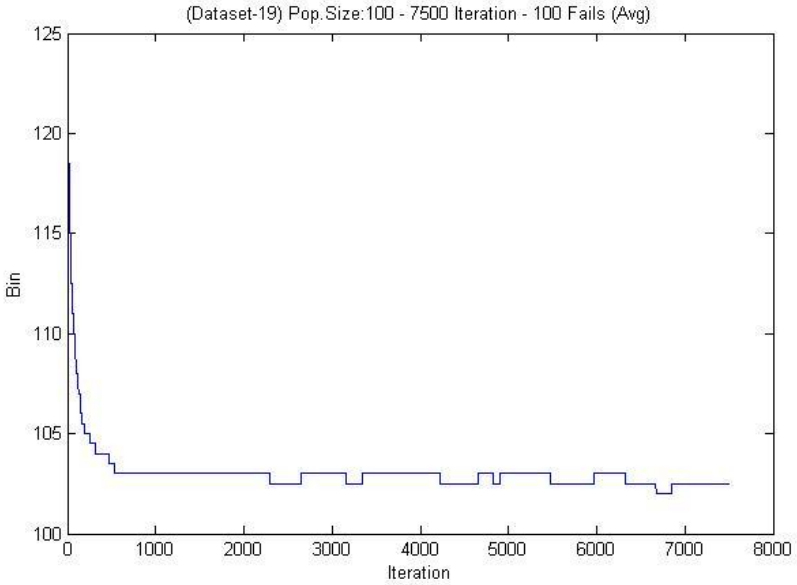

Fig. 10.A: Average Number of Bin for Table 10.E

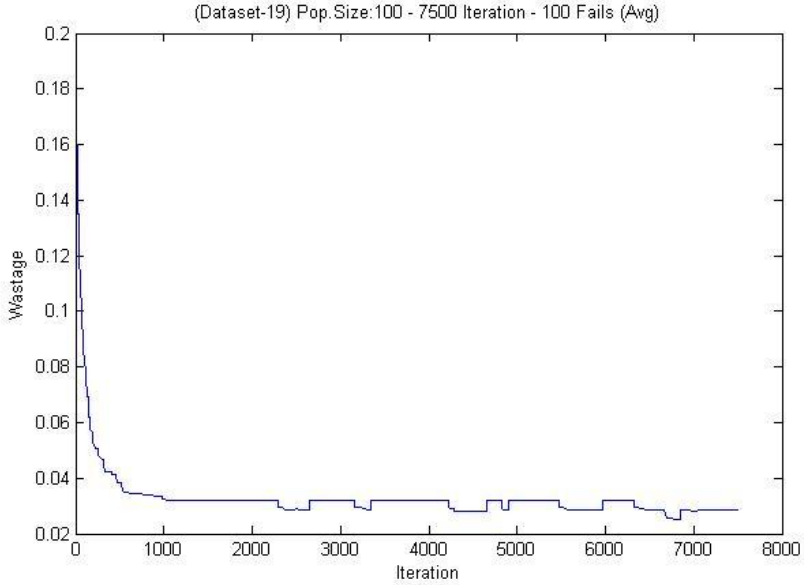

Fig. 10.B: Average Wastage for Table 10.E

Table 11: Results of Classic ABC Algorithm and MEABC Algorithm for Itemset-3

			BIN	WASTAGE	TIME
ABC	DS3	100-7500-100	207	0.0280	5.8826e+03
MEABC	DS3	100-7500-100-1500	207	0.0280	5.7224e+03
ABC	DS10	100-7500-100	207	0.0287	5.6019e+03
MEABC	DS10	100-7500-100-1500	207	0.0287	5.5787e+03
ABC	DS11	100-7500-100	204	0.0253	5.5568e+03
MEABC	DS11	100-7500-100-1500	205	0.0289	5.3168e+03
ABC	DS13	100-7500-100	205	0.0311	5.5264e+03
MEABC	DS13	100-7500-100-1500	204	0.0264	5.4918e+03
ABC	DS20	100-7500-100	201	0.0267	5.5251e+03
MEABC	DS20	100-7500-100-1500	201	0.0281	5.4196e+03

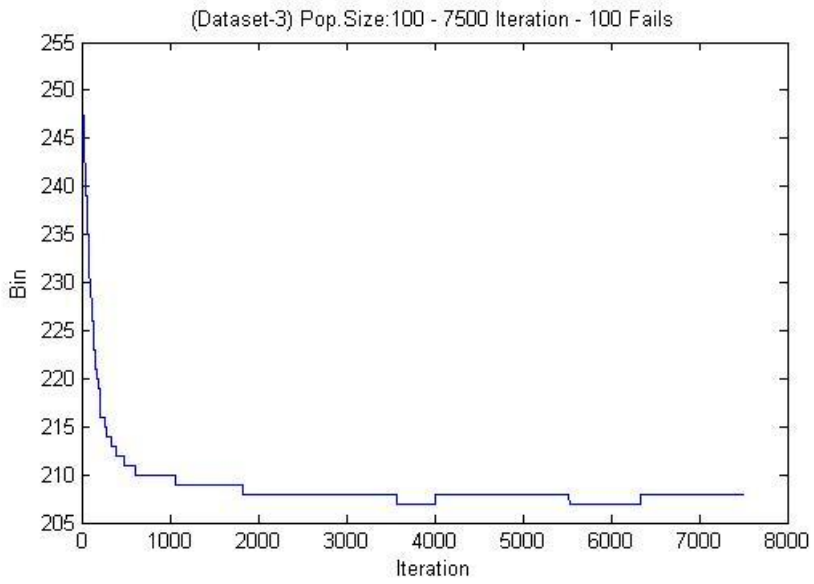

Fig. 11.A: ABC Results for Number of Bin for Group-3 in Table 11

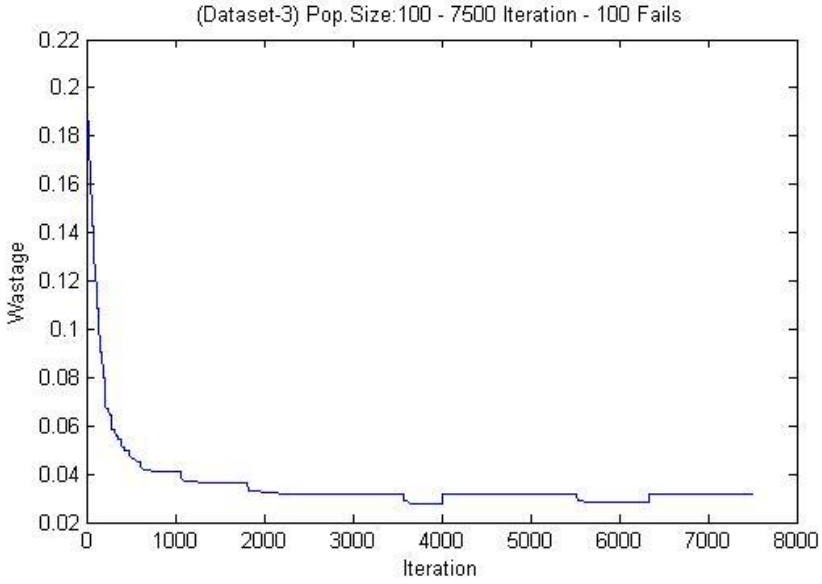

Fig. 11.B: ABC Results for Wastage for Group-3 in Table 11

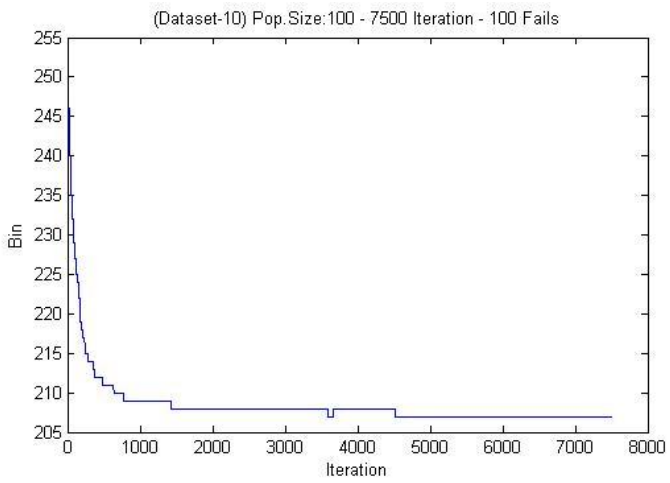

Fig. 12.A: ABC Results for Number of Bin for Group-10 in Table 11

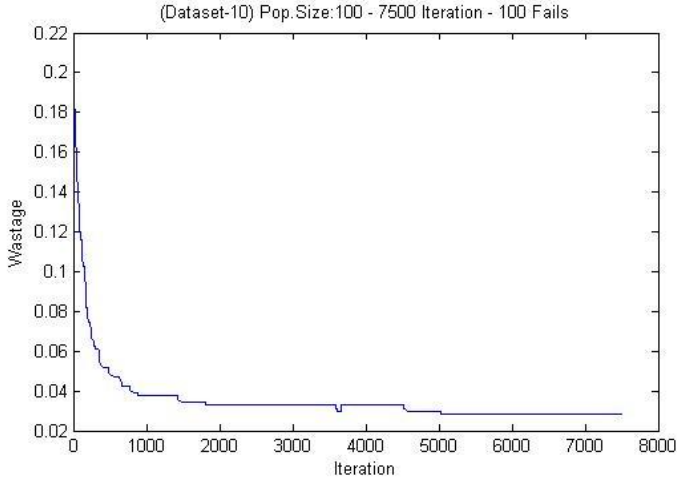

Fig. 12.B: ABC Results for Wastage for Group-10 in Table 11

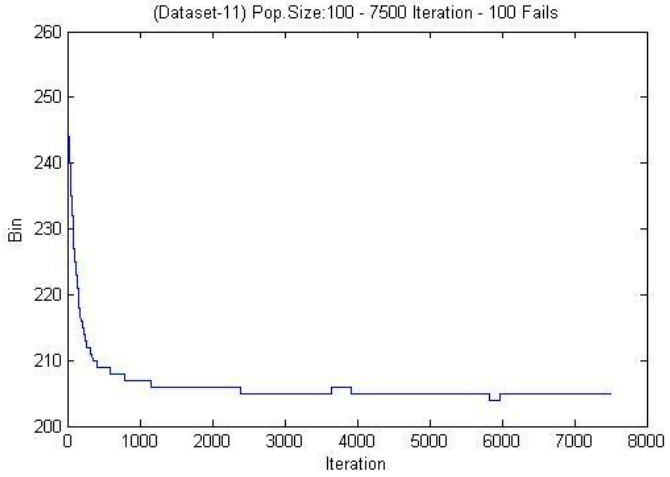

Fig. 13.A: ABC Results for Number of Bin for Group-11 in Table 11

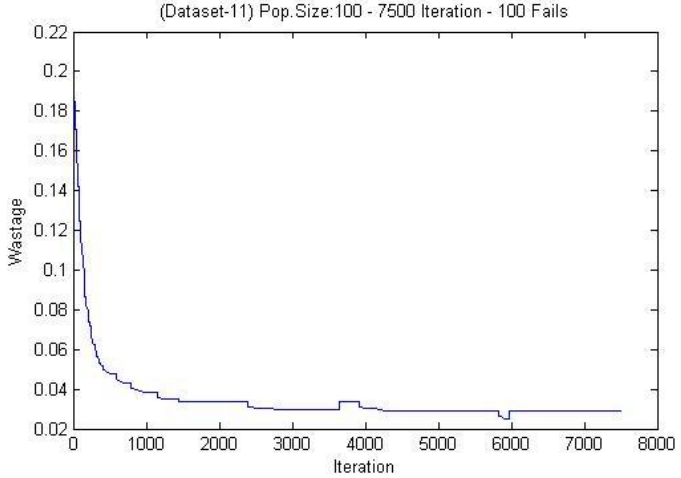

Fig. 13.B: ABC Results for Wastage for Group-11 in Table 11

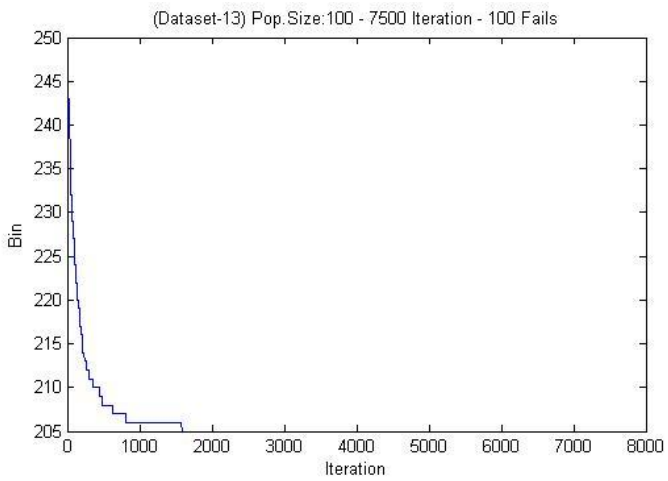

Fig. 14.A: ABC Results for Number of Bin for Group-13 in Table 11

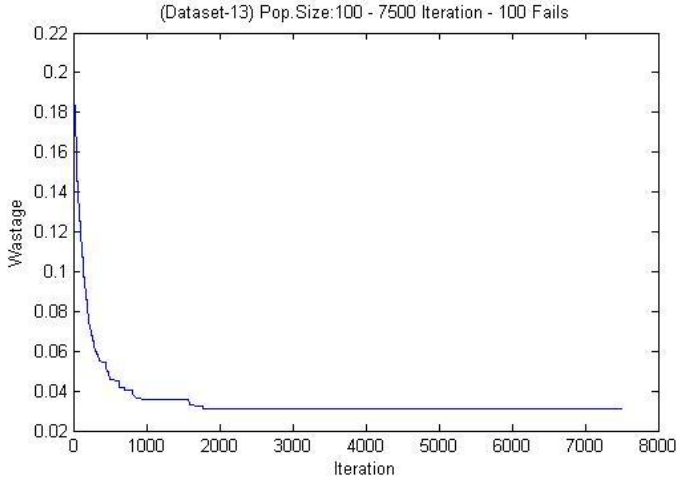

Fig. 14.B: ABC Results for Wastage for Group-13 in Table 11

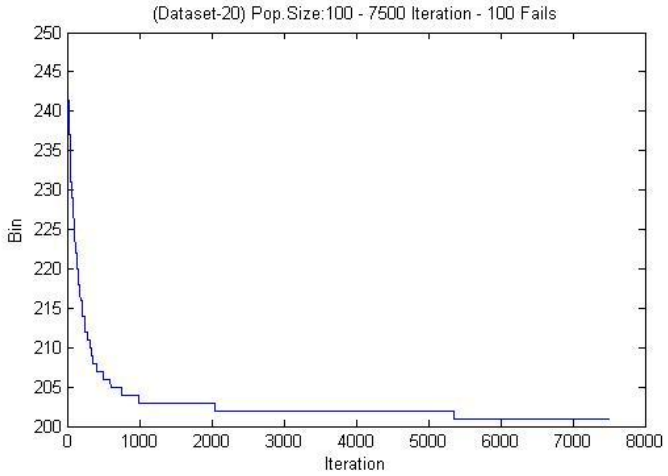

Fig. 15.A: ABC Results for Number of Bin for Group-20 in Table 11

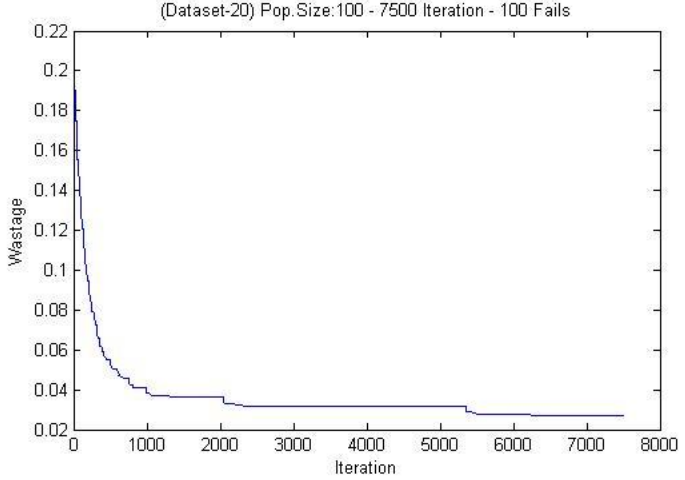

Fig. 15.B: ABC Results for Wastage for Group-20 in Table 11

Table 12: Results of Classic ABC Algorithm and MEABC Algorithm for Itemset-4

			BIN	WASTAGE	TIME
ABC	DS1	100-7500-100	411	0.0306	1.4936e+04
MEABC	DS1	100-7500-100-1500	411	0.0306	1.4848e+04
ABC	DS7	100-7500-100	406	0.0290	1.5399e+04
MEABC	DS7	100-7500-100-1500	406	0.0290	1.5212e+04
ABC	DS8	100-7500-100	415	0.0293	1.4673e+04
MEABC	DS8	100-7500-100-1500	415	0.0290	1.4438e+04
ABC	DS12	100-7500-100	413	0.0302	1.5030e+04
MEABC	DS12	100-7500-100-1500	413	0.0302	1.4836e+04
ABC	DS17	100-7500-100	416	0.0312	1.4946e+04
MEABC	DS17	100-7500-100-1500	415	0.0289	1.3447e+04

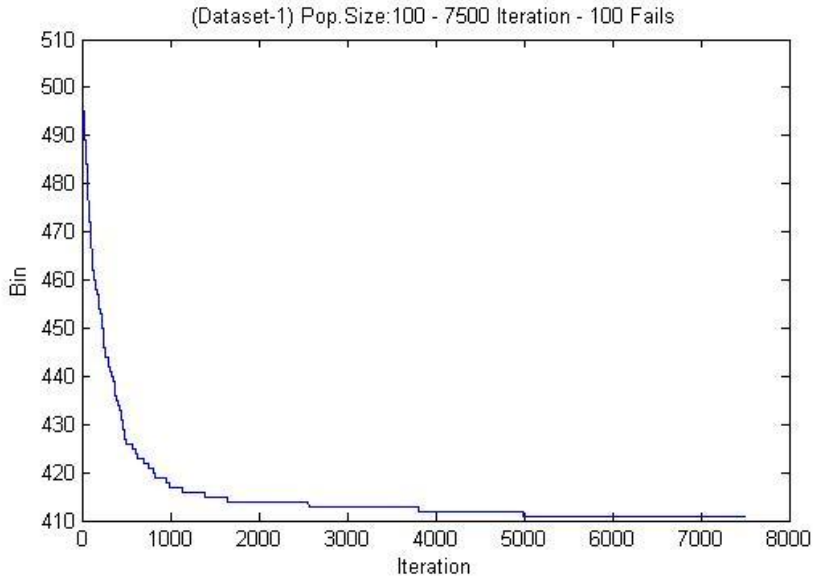

Fig. 16.A: ABC Results for Number of Bin for Group-1 in Table 12

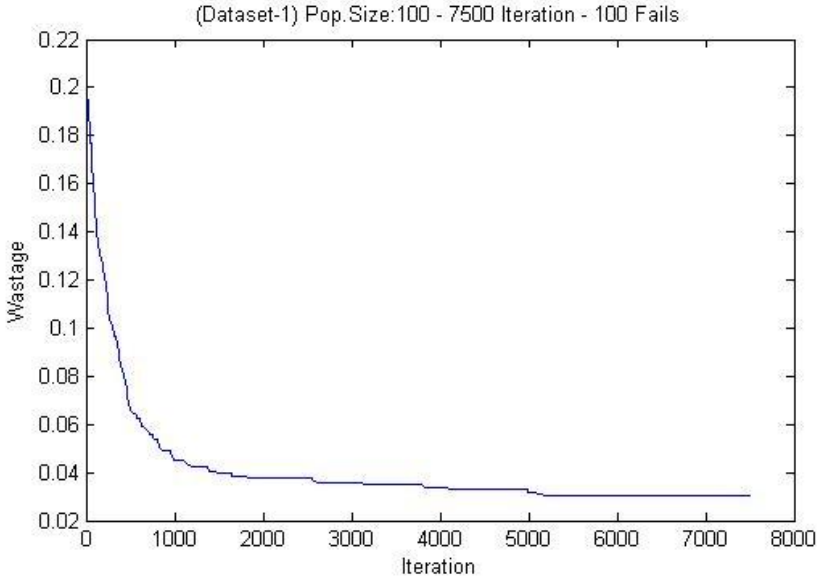

Fig. 16.B: ABC Results for Wastage for Group-1 in Table 12

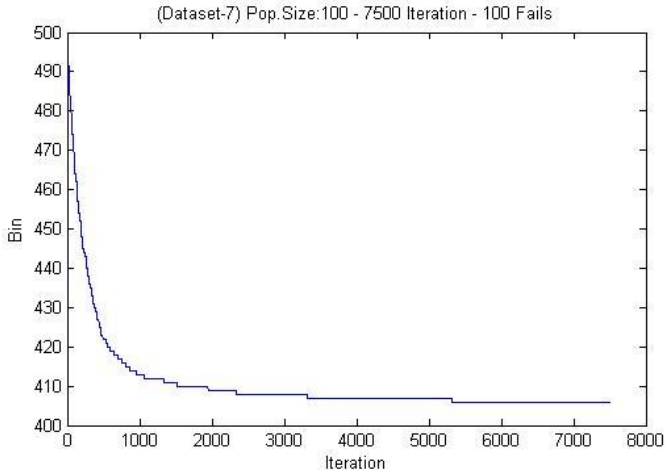

Fig. 17.A: ABC Results for Number of Bin for Group-7 in Table 12

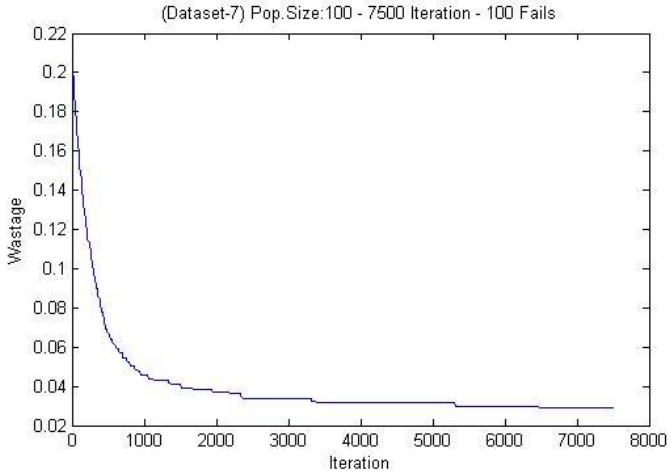

Fig. 17.B: ABC Results for Wastage for Group-7 in Table 12

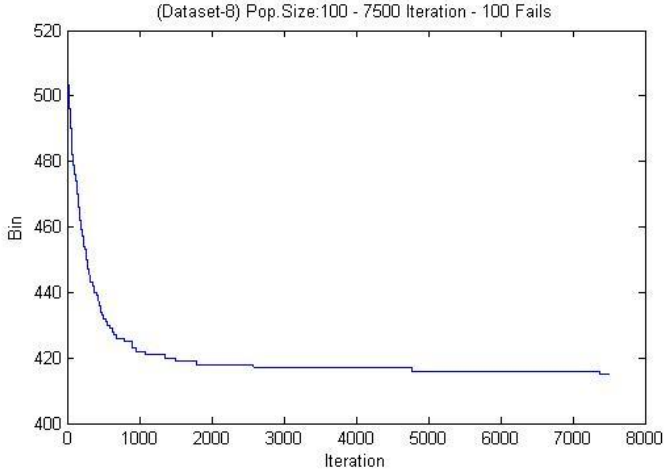

Fig. 18.A: ABC Results for Number of Bin for Group-20 in Table 12

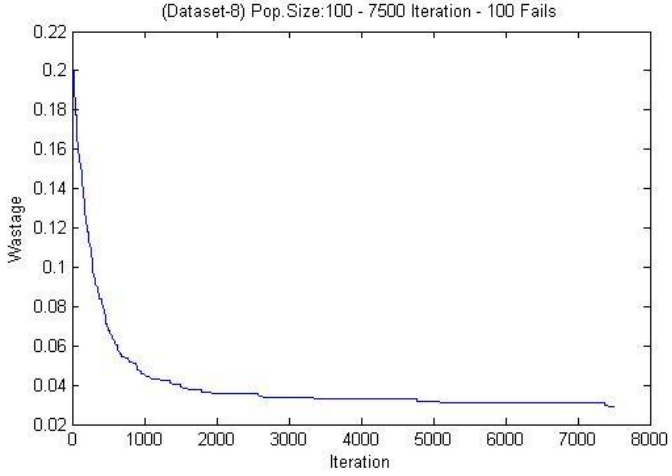

Fig. 18.B: ABC Results for Wastage for Group-20 in Table 12

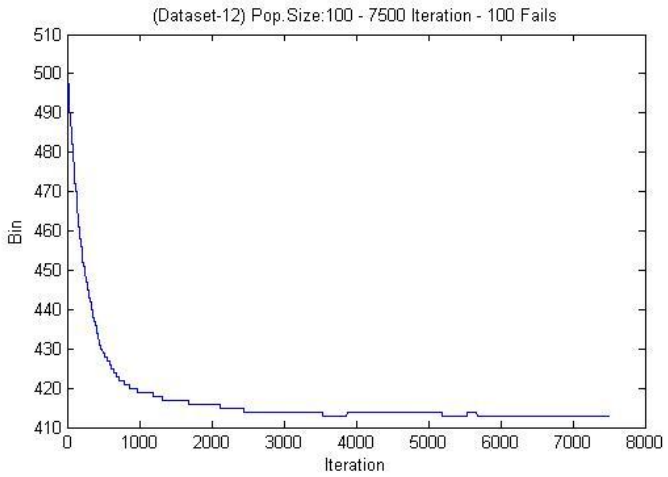

Fig. 19.A: ABC Results for Number of Bin for Group-12 in Table 12

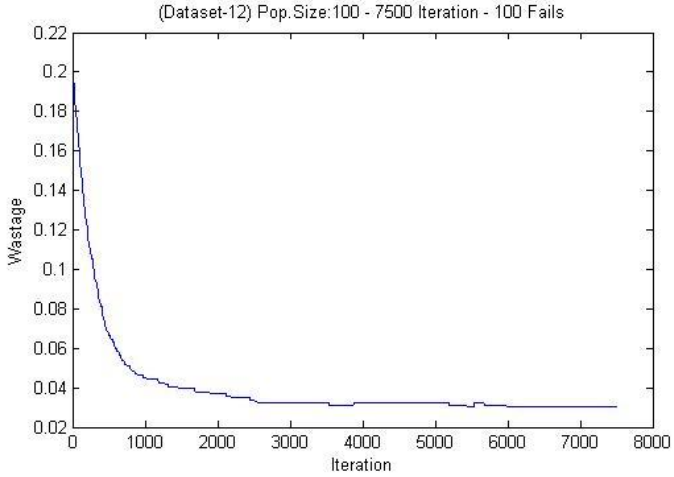

Fig. 19.B: ABC Results for Wastage for Group-12 in Table 12

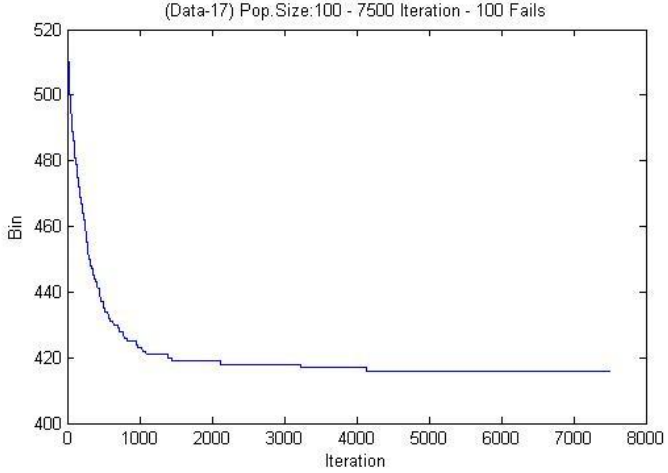

Fig. 20.A: ABC Results for Number of Bin for Group-17 in Table 12

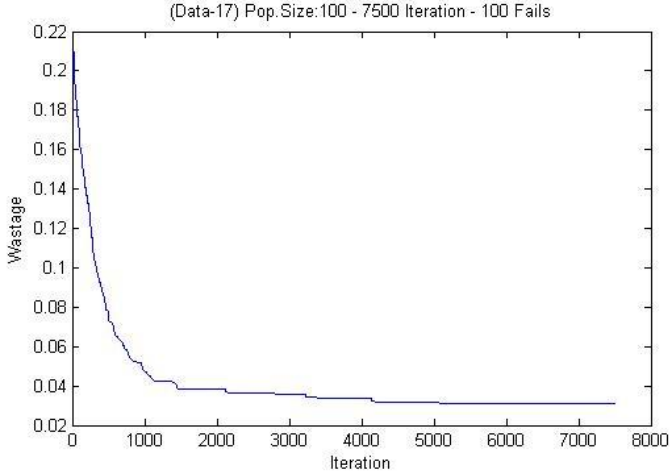

Fig. 20.B: ABC Results for Wastage for Group-17 in Table 12

Table 13.A: Results of Classic ABC Algorithm for Itemset-5 Group-2

Swarm:100 Iteration:7500 Max Number of Fail:100 Minimum Bin Usage Ratio:0.50 Group:2 Optimum Number of Bin:20																		
Test	1		2		3		4		5		OVERALL							
Time(sc)	457.2261		462.4832		461.3166		469.2675		472.8706		BIN				WASTE			
	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Best	No.Best	Mean	St. Dev.	Best	No.Best	Mean	St. Dev.
Best	21	0.0476	21	0.0476	21	0.0476	20	0.0198	21	0.0476	20	1	20.8	0.4472	0.0198	1	0.0420	0.0124
Mean	21.001	0.0478	21.002	0.0478	21.002	0.0478	20.989	0.0474	21.002	0.0478	20.989	1	20.9993	0.0059	0.0474	1	0.0477	0.0002
St. Dev.	0.0462	0.0025	0.0541	0.0027	0.0541	0.0027	0.1286	0.0042	0.0516	0.0025	0.0462	1	0.0669	0.0346	0.0025	2	0.0029	0.0007

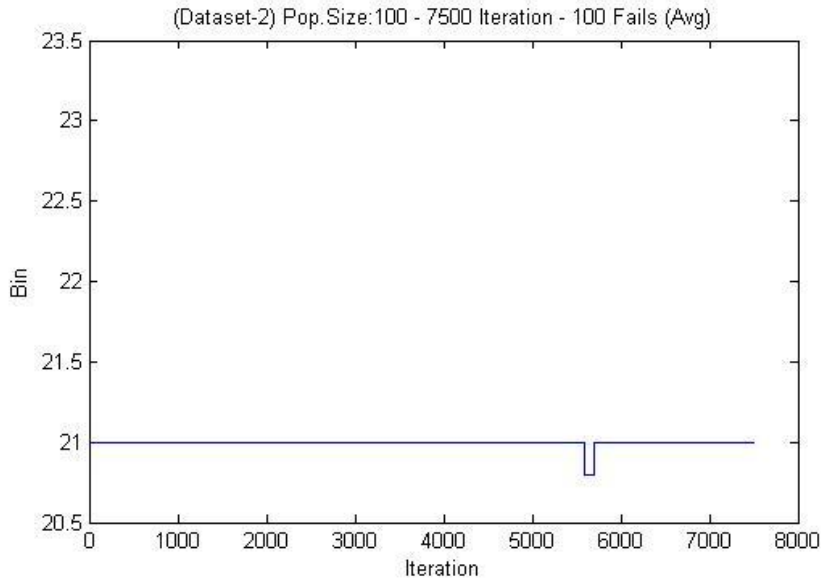

Fig. 21.A: Average Number of Bin for Table 13.A

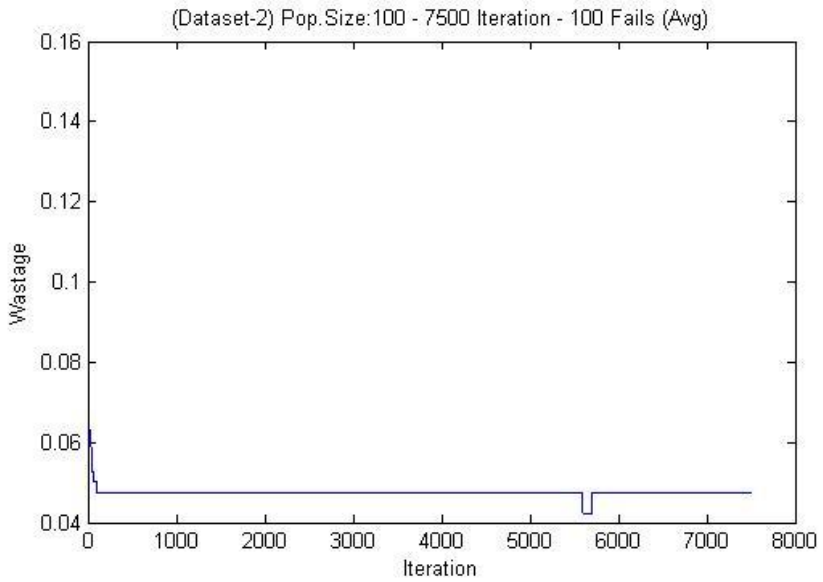

Fig. 21.B: Average Wastage for Table 13.A

Table 13.B: Results of Classic ABC Algorithm for Itemset-5 Group-4

Swarm:100 Iteration:7500 Max Number of Fail:100 Minimum Bin Usage Ratio:0.50 Group:4 Optimum Number of Bin:20																		
Test	1		2		3		4		5		OVERALL							
Time(sc)	457.0659		457.346		471.6333		457.2749		454.2206		BIN				WASTE			
	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Best	No.Best	Mean	St. Dev.	Best	No.Best	Mean	St. Dev.
Best	21	0.0476	21	0.0476	21	0.0476	20	0.0228	21	0.0476	20	1	20.8	0.4472	0.0228	1	0.0426	0.0111
Mean	21.002	0.0483	21.002	0.0481	21.001	0.0477	20.971	0.047	21.002	0.0477	20.9711	1	20.9956	0.0137	0.0470	1	0.0478	0.0005
St. Dev.	0.0529	0.0036	0.0476	0.0031	0.0462	0.0024	0.1872	0.0052	0.0462	0.0024	0.0462	2	0.0760	0.0622	0.0024	2	0.0033	0.0012

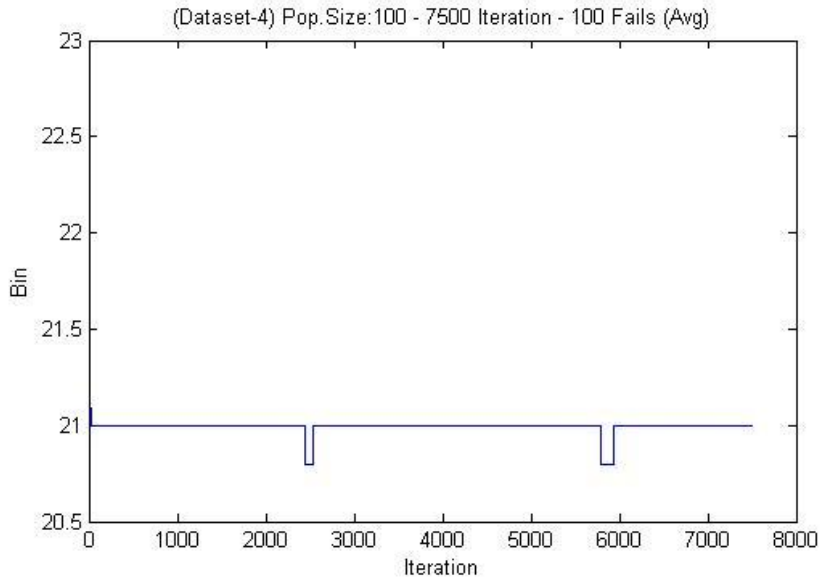

Fig. 22.A: Average Number of Bin for Table 13.B

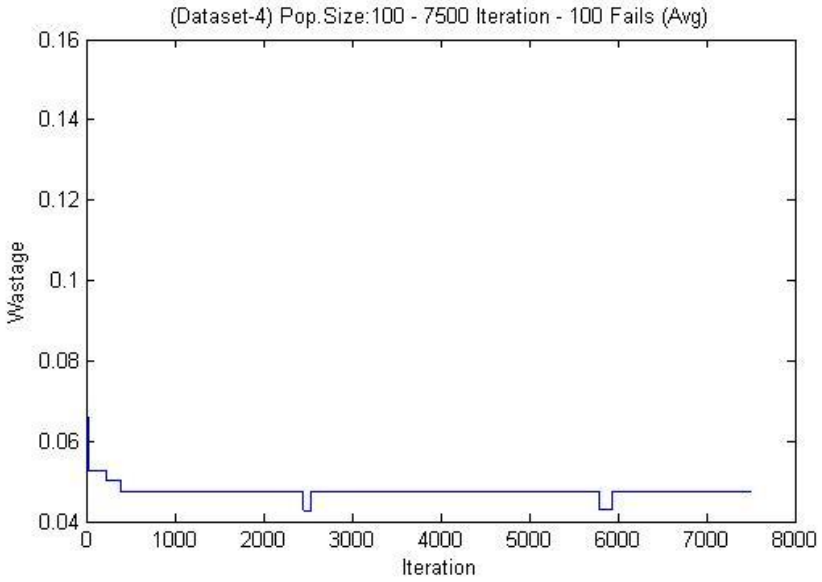

Fig. 22.B: Average Wastage for Table 13.B

Table 13.C: Results of Classic ABC Algorithm for Itemset-5 Group-9

Swarm:100 Iteration:7500 Max Number of Fail:100 Minimum Bin Usage Ratio:0.50 Group:9 Optimum Number of Bin:20																		
Test	1		2		3		4		5		OVERALL							
Time(sc)	421.8013		422.6551		422.7184		422.4861		439.1366		BIN				WASTE			
	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Best	No.Best	Mean	St. Dev.	Best	No.Best	Mean	St. Dev.
Best	20	0.0234	20	0.0227	21	0.0476	21	0.0476	21	0.0476	20	2	20.6	0.5477	0.0227	1	0.0378	0.0134
Mean	20.927	0.0459	20.991	0.0475	21.001	0.0477	21.002	0.0478	21.002	0.0478	20.9267	1	20.9844	0.0326	0.0459	1	0.0473	0.0008
St. Dev.	0.2683	0.0067	0.111	0.0035	0.0365	0.0018	0.0447	0.0024	0.0503	0.0024	0.0365	1	0.1022	0.0974	0.0018	1	0.0034	0.0020

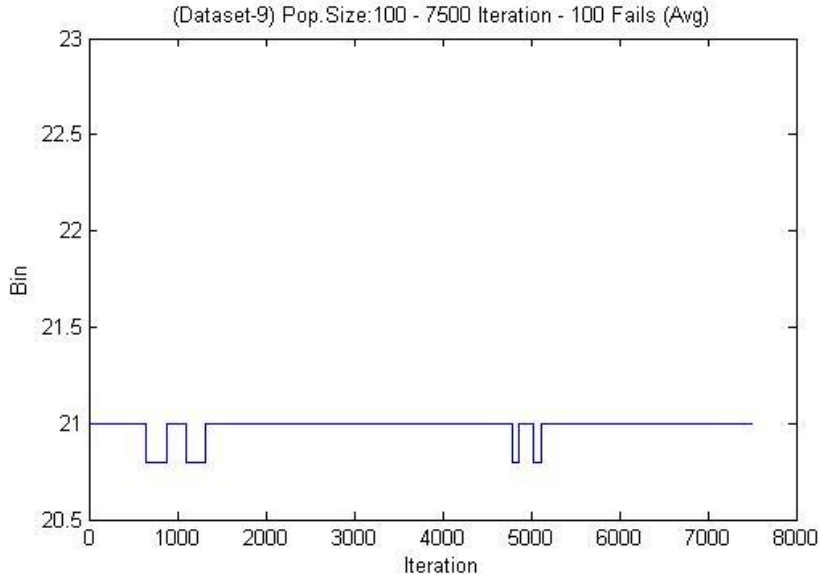

Fig. 23.A: Average Number of Bin for Table 13.C

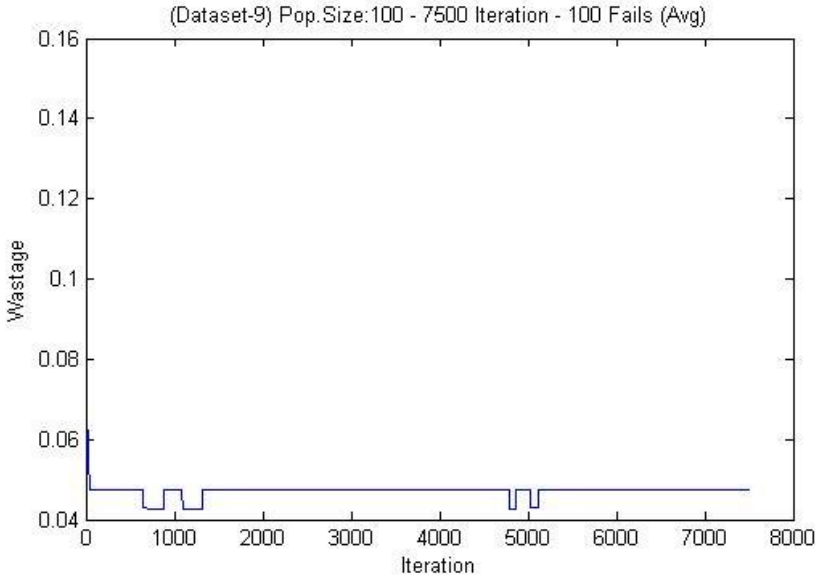

Fig. 23.B: Average Wastage for Table 13.C

Table 13.D: Results of Classic ABC Algorithm for Itemset-5 Group-15

Swarm:100 Iteration:7500 Max Number of Fail:100 Minimum Bin Usage Ratio:0.50 Group:15 Optimum Number of Bin:20																			
Test	1		2		3		4		5		OVERALL								
Time(sc)	479.7274		503.2211		499.5773		501.9112		504.3433		BIN				WASTE				
	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Best	No.Best	Mean	St. Dev.	Best	No.Best	Mean	St. Dev.
Best	21	0.0476	20	0.0237	21	0.0476	20	0.0232	21	0.0476	20	2	20.6	0.5477	0.0232	1	0.0379	0.0132
Mean	21.002	0.0478	20.969	0.047	21.003	0.0478	20.981	0.0472	21.003	0.048	20.9685	1	20.9914	0.0158	0.0470	1	0.0476	0.0004
St. Dev.	0.0565	0.0028	0.1892	0.0051	0.0577	0.0029	0.1551	0.0044	0.06	0.0033	0.0565	1	0.1037	0.0637	0.0028	1	0.0037	0.0010

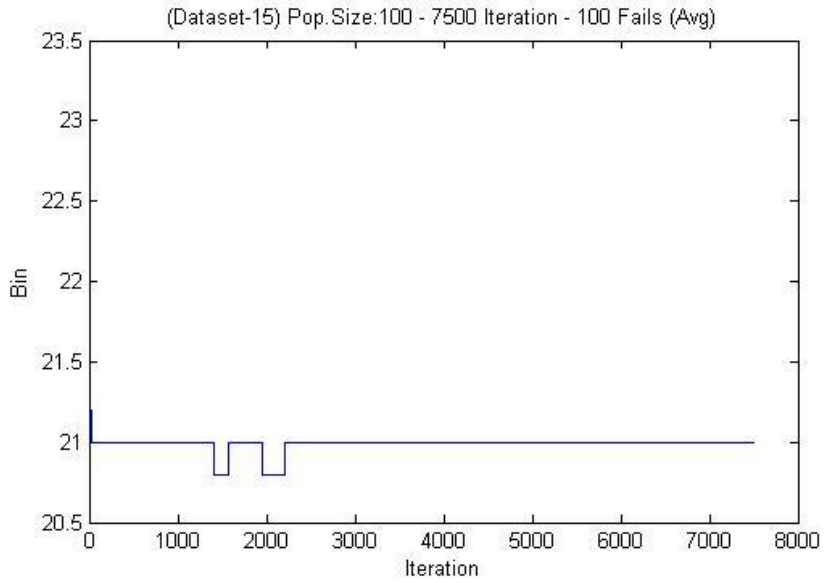

Fig. 24.A: Average Number of Bin for Table 13.D

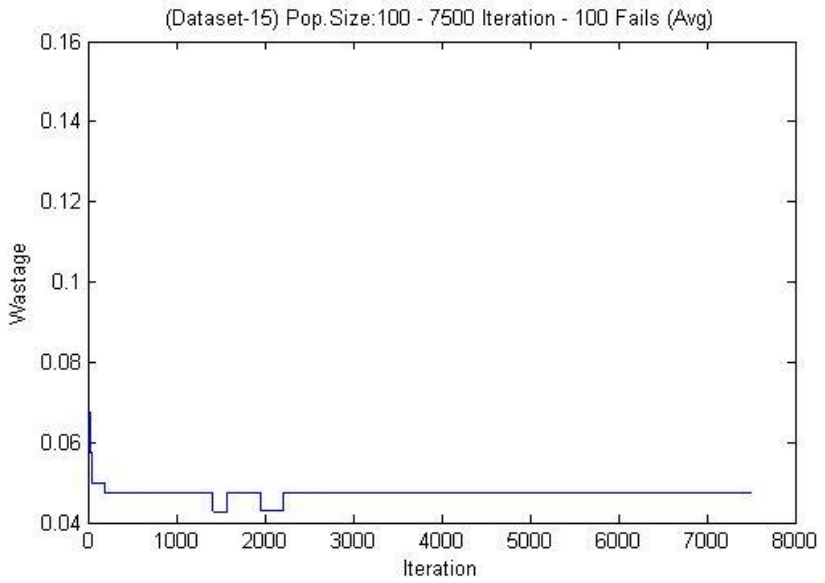

Fig. 24.B: Average Wastage for Table 13.D

Table 13.E: Results of Classic ABC Algorithm for Itemset-5 Group-18

Swarm:100 Iteration:7500 Max Number of Fail:100 Minimum Bin Usage Ratio:0.50 Group:18 Optimum Number of Bin:20																		
Test	1		2		3		4		5		OVERALL							
Time(sc)	436.6198		437.2098		461.036		475.4929		474.1831		BIN				WASTE			
	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Best	No.Best	Mean	St. Dev.	Best	No.Best	Mean	St. Dev.
Best	20	0.0234	21	0.0476	21	0.0476	21	0.0476	21	0.0476	20	1	20.8	0.4472	0.0234	1	0.0428	0.0108
Mean	20.946	0.0464	21.001	0.0478	21.003	0.0478	21.002	0.0478	21.003	0.0478	20.9457	1	20.9909	0.0253	0.0464	1	0.0475	0.0006
St. Dev.	0.2397	0.0063	0.04	0.0024	0.0588	0.0028	0.0577	0.0027	0.0653	0.0031	0.0400	1	0.0923	0.0829	0.0024	1	0.0035	0.0016

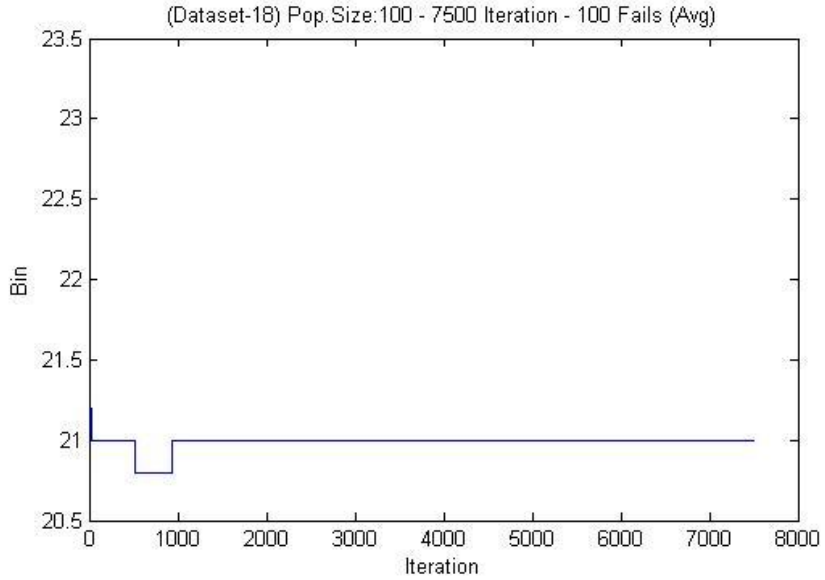

Fig. 25.A: Average Number of Bin for Table 13.E

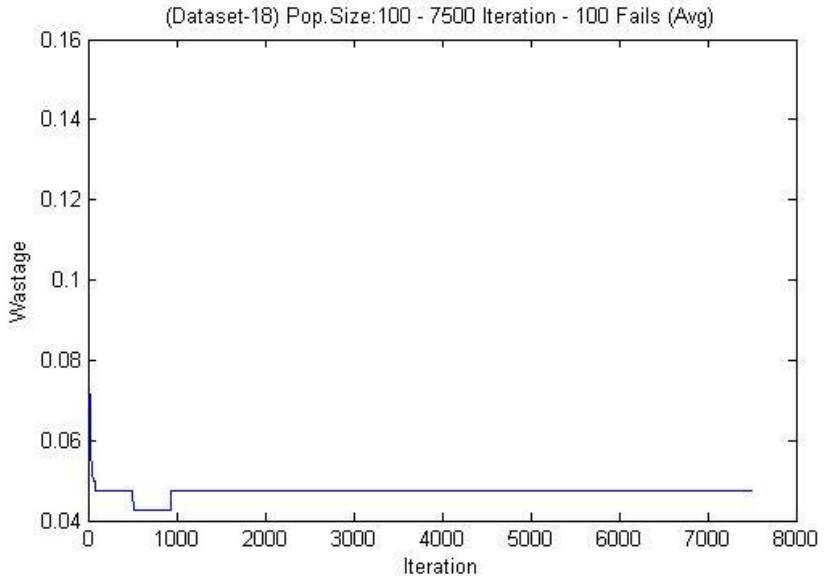

Fig. 25.B: Average Wastage for Table 13.E

Table 14.A: Results of Classic ABC Algorithm for Itemset-6 Group-2

Swarm:100 Iteration:7500 Max Number of Fail:100 Minimum Bin Usage Ratio:0.50 Group:2 Optimum Number of Bin:40																		
Test	1		2		3		4		5		OVERALL							
Time(sc)	916.9337		917.1444		912.4433		910.5781		919.3476		BIN				WASTE			
	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Best	No.Best	Mean	St. Dev.	Best	No.Best	Mean	St. Dev.
Best	42	0.0476	42	0.0476	41	0.0348	42	0.0476	42	0.0476	41	1	41.8	0.4472	0.0348	1	0.0451	0.0057
Mean	42.016	0.0481	42.011	0.0479	42.005	0.0479	42.011	0.0479	42.016	0.0481	42.005	1	42.012	0.0045	0.0479	1	0.0480	0.0001
St. Dev.	0.2123	0.0048	0.1808	0.0040	0.2122	0.0045	0.1808	0.0040	0.2123	0.0048	0.1808	2	0.1997	0.0172	0.0040	2	0.0044	0.0004

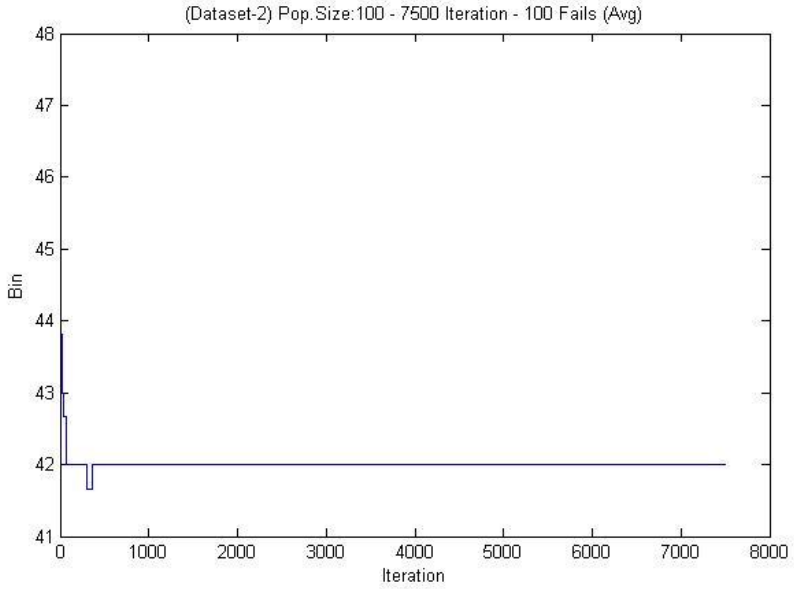

Fig. 26.A: Average Number of Bin for Table 14.A

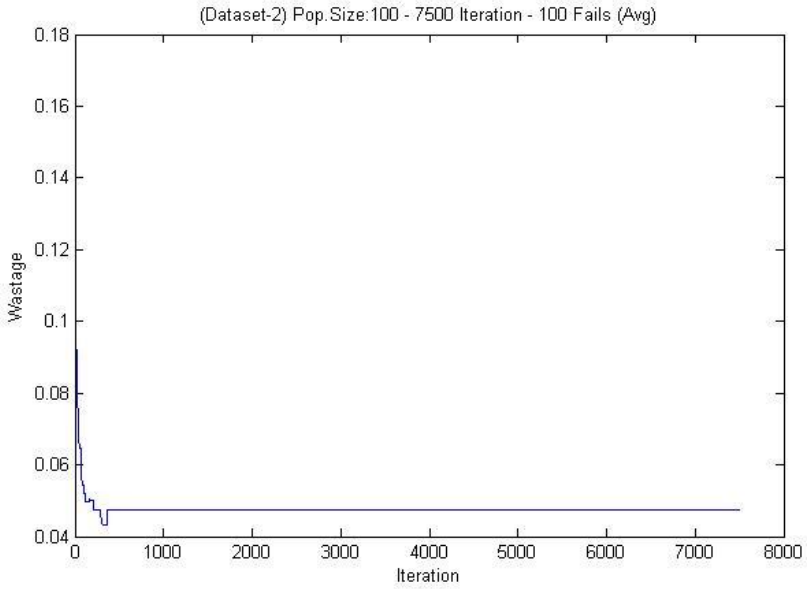

Fig. 26.B: Average Wastage for Table 14.A

Table 14.B: Results of Classic ABC Algorithm for Itemset-6 Group-3

Swarm:100 Iteration:7500 Max Number of Fail:100 Minimum Bin Usage Ratio:0.50 Group:3 Optimum Number of Bin:40																		
Test	1		2		3		4		5		OVERALL							
Time(sc)	919.4462		919.9926		941.0009		935.6478		925.2179		BIN				WASTE			
	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Best	No.Best	Mean	St. Dev.	Best	No.Best	Mean	St. Dev.
Best	42	0.0476	42	0.0476	42	0.0476	42	0.0476	42	0.0476	42	5	42	0.0000	0.0476	1	0.0476	0.0000
Mean	42.014	0.0482	42.022	0.0485	42.014	0.0480	42.037	0.0494	42.014	0.0482	42.014	2	42.020	0.0102	0.0480	1	0.0484	0.0006
St. Dev.	0.2019	0.0046	0.2210	0.0052	0.1864	0.0042	0.2596	0.0060	0.2019	0.0046	0.1864	1	0.2142	0.0282	0.0042	1	0.0049	0.0007

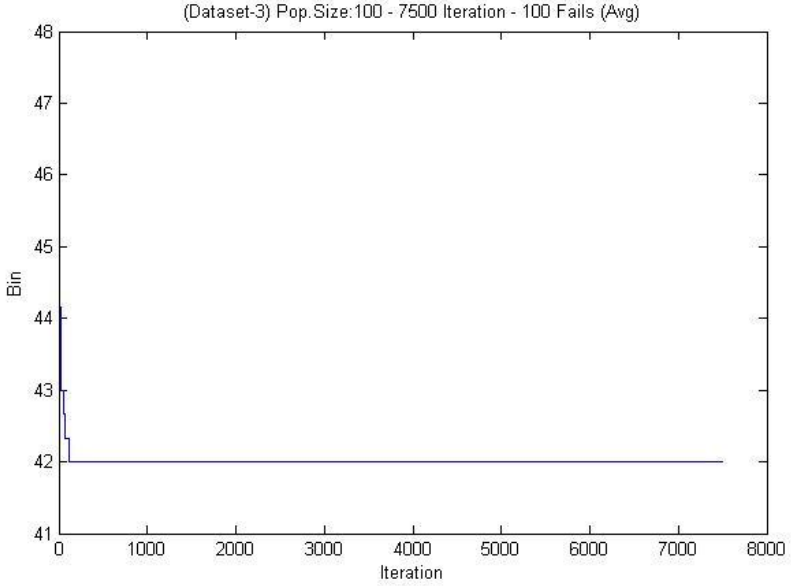

Fig. 27.A: Average Number of Bin for Table 14.B

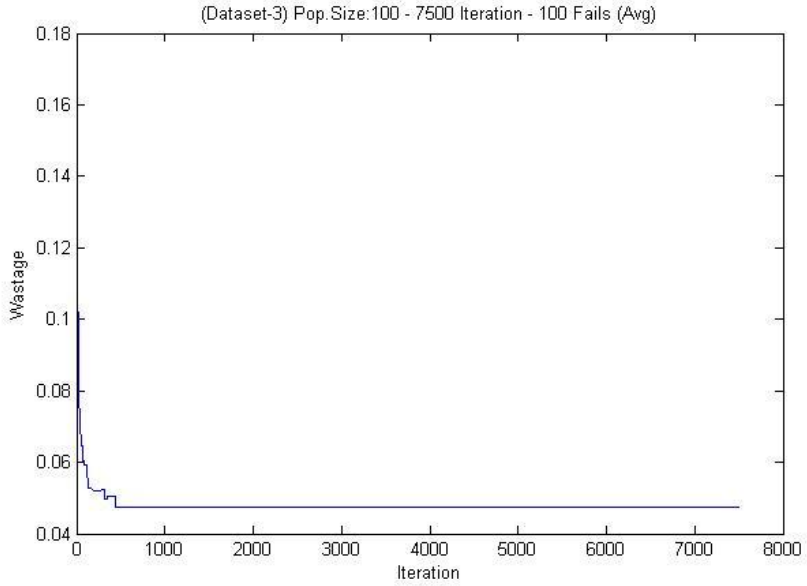

Fig. 27.B: Average Wastage for Table 14.B

Table 14.C: Results of Classic ABC Algorithm for Itemset-6 Group-5

Swarm:100 Iteration:7500 Max Number of Fail:100 Minimum Bin Usage Ratio:0.50 Group:5 Optimum Number of Bin:40																		
Test	1		2		3		4		5		OVERALL							
Time(sc)	931.7264		925.5368		919.1782		919.4462		935.6478		BIN				WASTE			
	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Best	No.Best	Mean	St. Dev.	Best	No.Best	Mean	St. Dev.
Best	42	0.0537	42	0.0537	42	0.0476	42	0.0476	42	0.0476	42	5	42	0.0000	0.0476	1	0.0500	0.0033
Mean	42.857	0.0677	42.774	0.0667	42.013	0.0480	42.011	0.0479	42.014	0.0482	42.011	1	42.334	0.4408	0.0479	1	0.0557	0.0105
St. Dev.	0.3816	0.0061	0.4474	0.0067	0.1868	0.0043	0.1808	0.0040	0.2019	0.0046	0.1808	1	0.2797	0.1255	0.0040	1	0.0052	0.0012

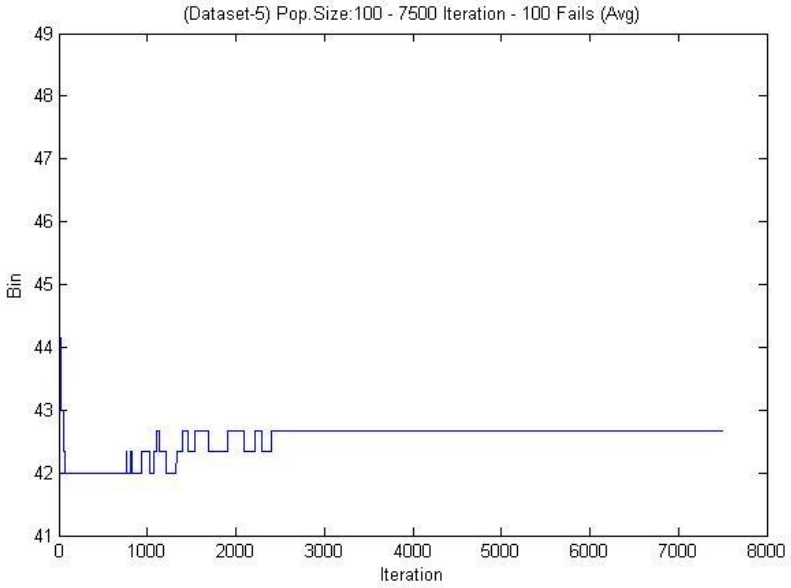

Fig. 28.A: Average Number of Bin for Table 14.C

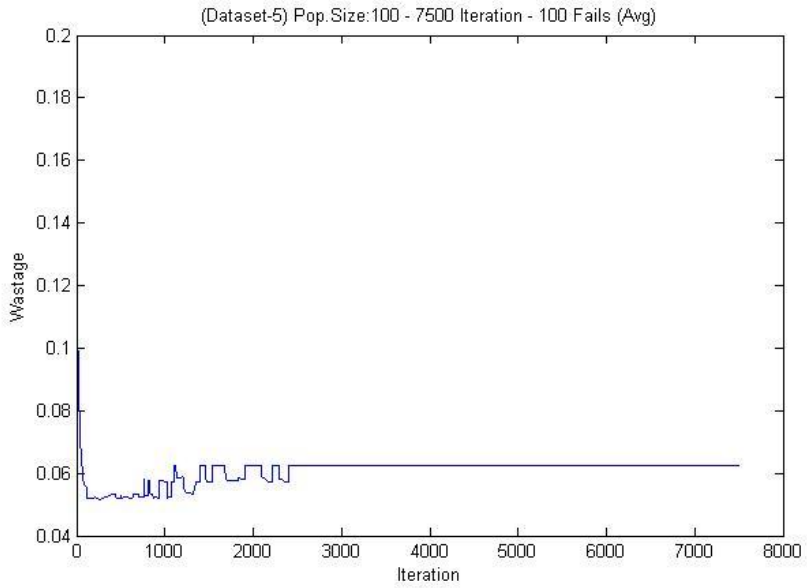

Fig. 28.B: Average Wastage for Table 14.C

Table 14.D: Results of Classic ABC Algorithm for Itemset-6 Group-14

Swarm:100 Iteration:7500 Max Number of Fail:100 Minimum Bin Usage Ratio:0.50 Group:14 Optimum Number of Bin:40																		
Test	1		2		3		4		5		OVERALL							
Time(sc)	1.01E+03		1.03E+03		993.7954		1.03E+03		925.5368		BIN				WASTE			
	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Best	No.Best	Mean	St. Dev.	Best	No.Best	Mean	St. Dev.
Best	41	0.0335	41	0.0341	42	0.0536	42	0.0537	42	0.0476	41	2	41.6	0.5477	0.0335	1	0.0445	0.0100
Mean	41.990	0.0476	41.998	0.0480	42.804	0.0670	42.857	0.0677	42.016	0.0481	41.990	1	42.333	0.4546	0.0476	1	0.0557	0.0107
St. Dev.	0.2398	0.0046	0.2110	0.0044	0.4199	0.0064	0.3816	0.0061	0.2123	0.0048	0.2110	1	0.2929	0.1000	0.0044	1	0.0052	0.0009

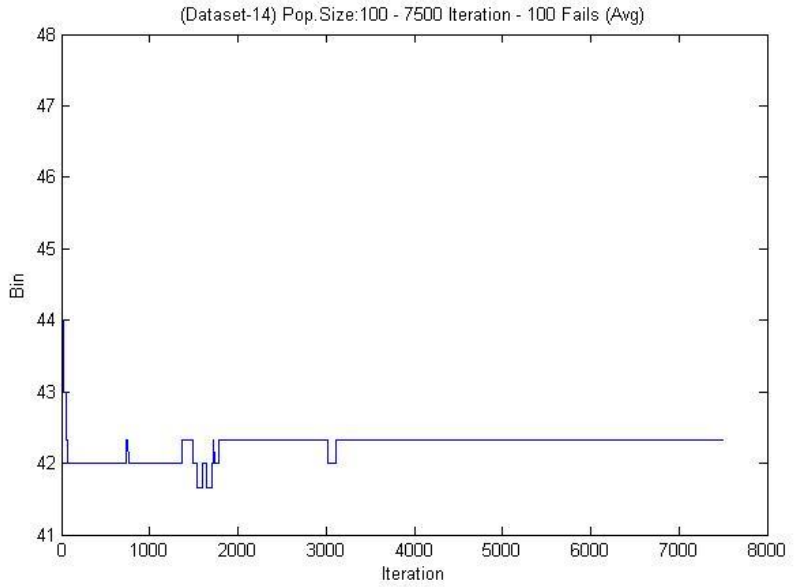

Fig. 29.A: Average Number of Bin for Table 14.D

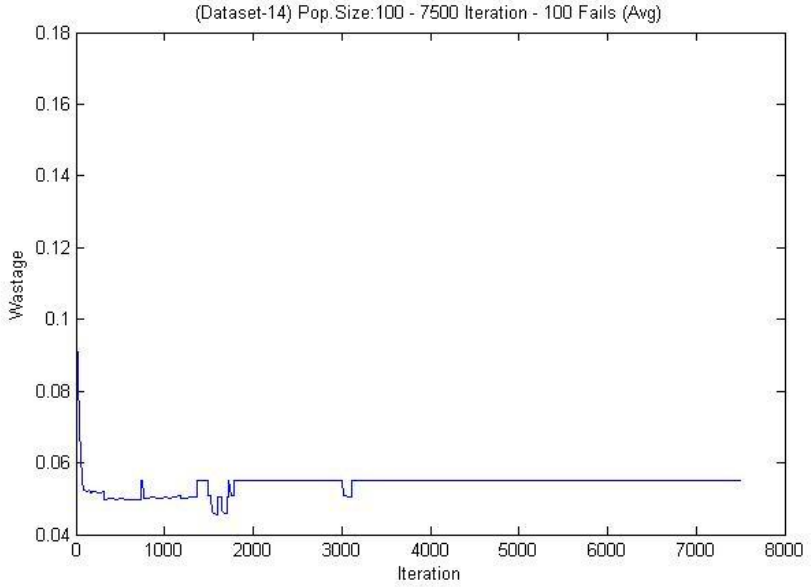

Fig. 29.B: Average Wastage for Table 14.D

Table 14.E: Results of Classic ABC Algorithm for Itemset-6 Group-18

Swarm:100 Iteration:7500 Max Number of Fail:100 Minimum Bin Usage Ratio:0.50 Group:18 Optimum Number of Bin:40																		
Test	1		2		3		4		5		OVERALL							
Time(sc)	1.16E+03		1.04E+03		1.05E+03		925.5368		919.1782		BIN				WASTE			
	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Best	No.Best	Mean	St. Dev.	Best	No.Best	Mean	St. Dev.
Best	42	0.0476	42	0.0537	41	0.0338	42	0.0476	42	0.0476	41	1	41.8	0.4472	0.0338	1	0.0461	0.0074
Mean	42.037	0.0494	42.706	0.0656	42.809	0.0669	42.037	0.0494	42.016	0.0481	42.016	1	42.321	0.4002	0.0481	1	0.0559	0.0095
St. Dev.	0.2596	0.0060	0.4792	0.0072	0.4633	0.0078	0.2596	0.0060	0.2123	0.0048	0.2123	1	0.3348	0.1262	0.0048	1	0.0064	0.0012

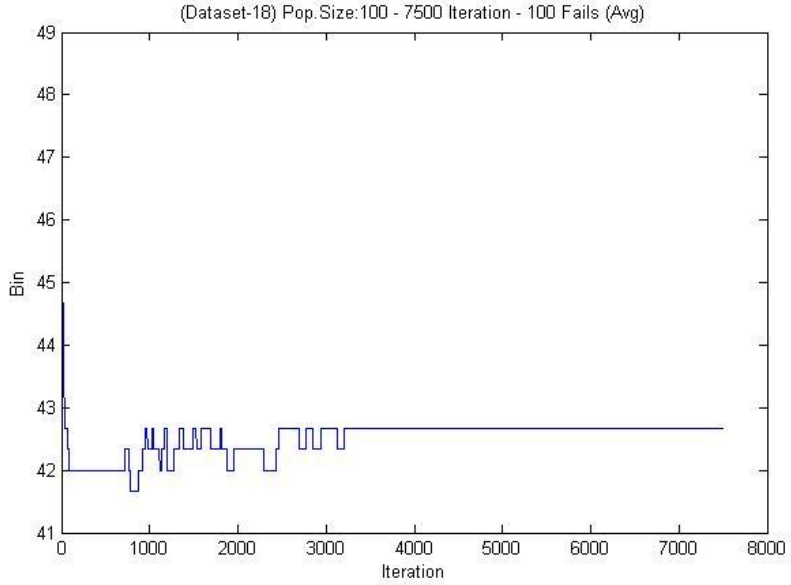

Fig. 30.A: Average Number of Bin for Table 14.E

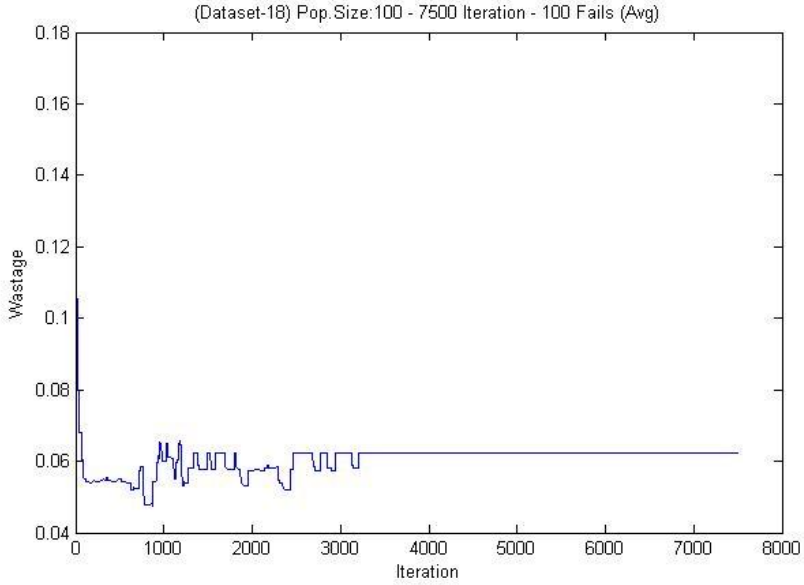

Fig. 30.B: Average Wastage for Table 14.E

Table 15.A: Results of Classic ABC Algorithm for Itemset-7 Group-1

Swarm:100 Iteration:7500 Max Number of Fail:100 Minimum Bin Usage Ratio:0.50 Group:1 Optimum Number of Bin:83																		
Test	1		2		3		4		5		OVERALL							
Time(sc)	2.11E+03		2.07E+03		2.11E+03		2.12E+03		2.09E+03		BIN				WASTE			
	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Best	No.Best	Mean	St. Dev.	Best	No.Best	Mean	St. Dev.
Best	87	0.0500	87	0.0494	87	0.0500	87	0.0500	87	0.0500	87	5	87	0.0000	0.0494	1	0.0498	0.0003
Mean	88.030	0.0574	88.039	0.0576	88.029	0.0574	88.030	0.0574	88.029	0.0574	88.029	1	88.031	0.0042	0.0574	4	0.0574	0.0001
St. Dev.	0.6641	0.0065	0.6033	0.0061	0.6548	0.0048	0.6247	0.0042	0.6643	0.0059	0.6033	1	0.6422	0.0271	0.0042	1	0.0055	0.0010

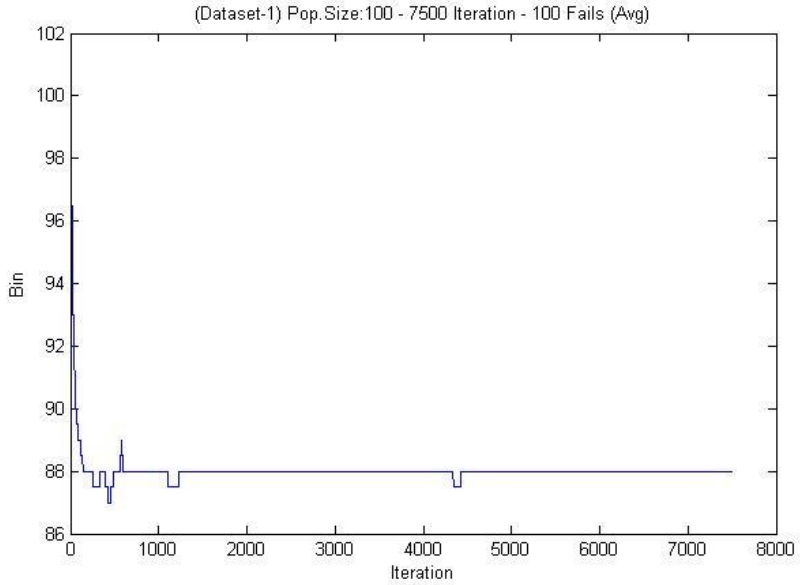

Fig. 31.A: Average Number of Bin for Table 15.A

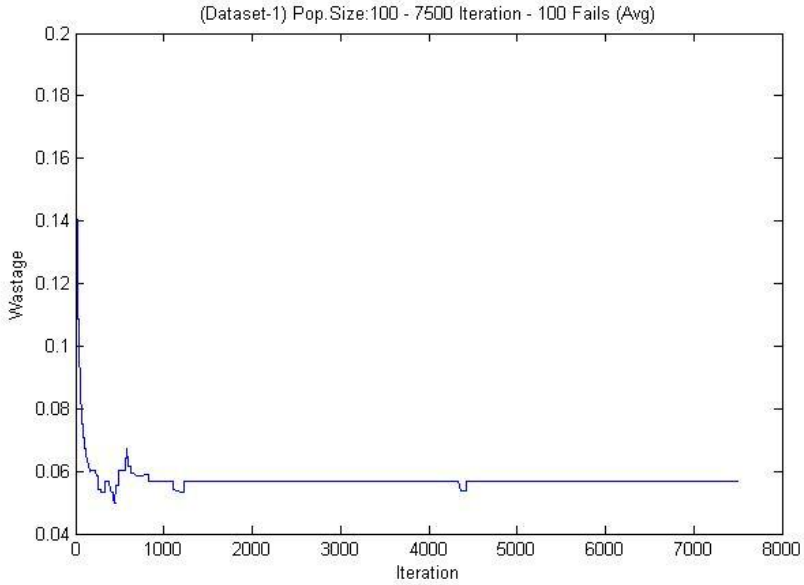

Fig. 31.B: Average Wastage for Table 15.A

Table 15.B: Results of Classic ABC Algorithm for Itemset-7 Group-4

Swarm:100 Iteration:7500 Max Number of Fail:100 Minimum Bin Usage Ratio:0.50 Group:4 Optimum Number of Bin:83																		
Test	1		2		3		4		5		OVERALL							
Time(sc)	2.02E+03		2.02E+03		2.02E+03		2.01E+03		2.16E+03		BIN				WASTE			
	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Best	No.Best	Mean	St. Dev.	Best	No.Best	Mean	St. Dev.
Best	87	0.0493	87	0.0507	87	0.0503	87	0.0526	87	0.0507	87	5	87	0.0000	0.0493	1	0.0507	0.0012
Mean	88.008	0.0572	88.848	0.0664	88.848	0.0652	88.184	0.0628	88.258	0.0662	88.008	1	88.429	0.3931	0.0572	1	0.0636	0.0038
St. Dev.	0.6262	0.0061	0.6915	0.0062	0.7426	0.0051	0.6471	0.0058	0.6572	0.0061	0.6262	1	0.6729	0.0455	0.0051	1	0.0059	0.0005

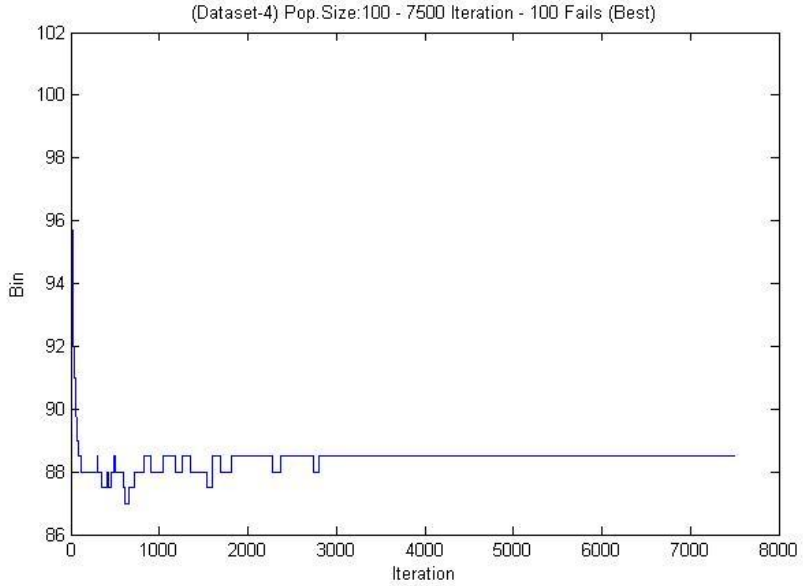

Fig. 32.A: Average Number of Bin for Table 15.B

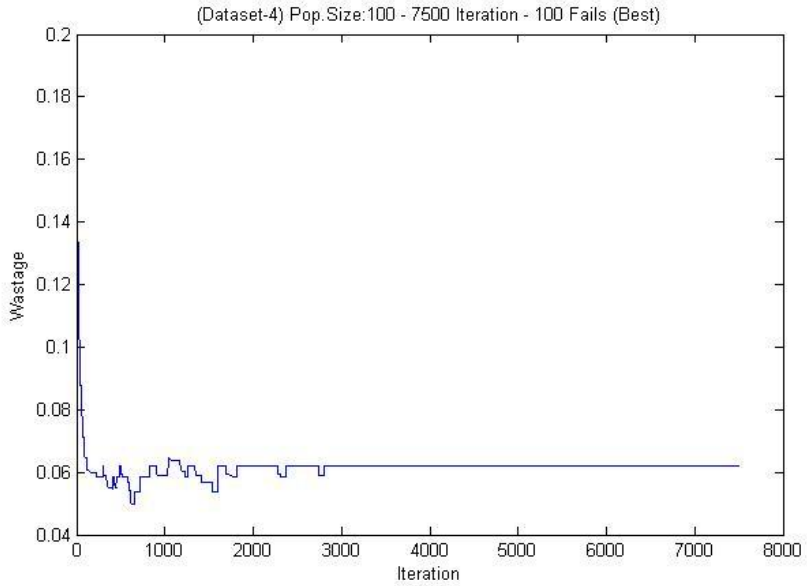

Fig. 32.B: Average Wastage for Table 15.B

Table 15.C: Results of Classic ABC Algorithm for Itemset-7 Group-9

Swarm:100 Iteration:7500 Max Number of Fail:100 Minimum Bin Usage Ratio:0.50 Group:9 Optimum Number of Bin:83																		
Test	1		2		3		4		5		OVERALL							
Time(sc)	2.07E+03		2.06E+03		2.08E+03		2.16E+03		2.01E+03		BIN				WASTE			
	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Best	No.Best	Mean	St. Dev.	Best	No.Best	Mean	St. Dev.
Best	87	0.0499	87	0.0498	87	0.0499	87	0.0499	87	0.0499	87	5	87	0.0000	0.0498	1	0.0499	0.0000
Mean	87.993	0.0570	88.032	0.0573	87.913	0.0587	87.812	0.0562	87.572	0.0471	87.572	1	87.865	0.1837	0.0471	1	0.0552	0.0046
St. Dev.	0.6522	0.0063	0.6230	0.0061	0.6522	0.0063	0.6522	0.0063	0.6522	0.0063	0.6230	1	0.6463	0.0131	0.0061	1	0.0063	0.0001

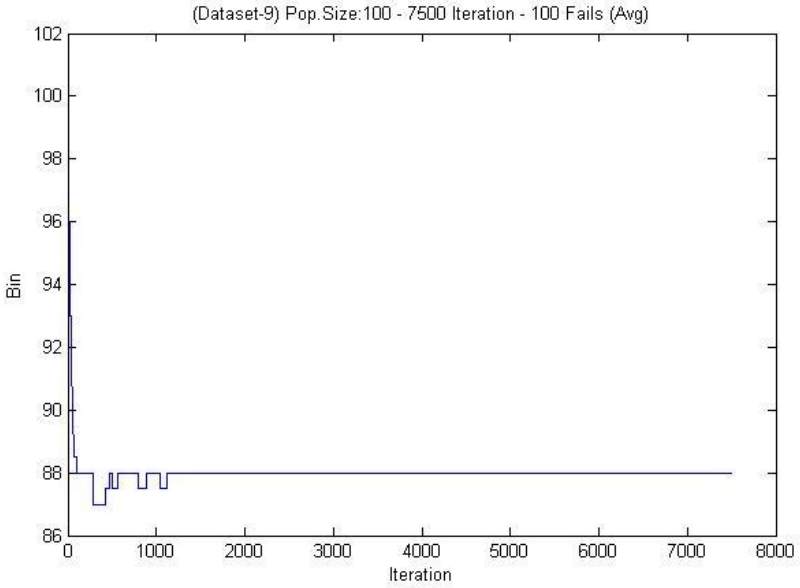

Fig. 33.A: Average Number of Bin for Table 15.C

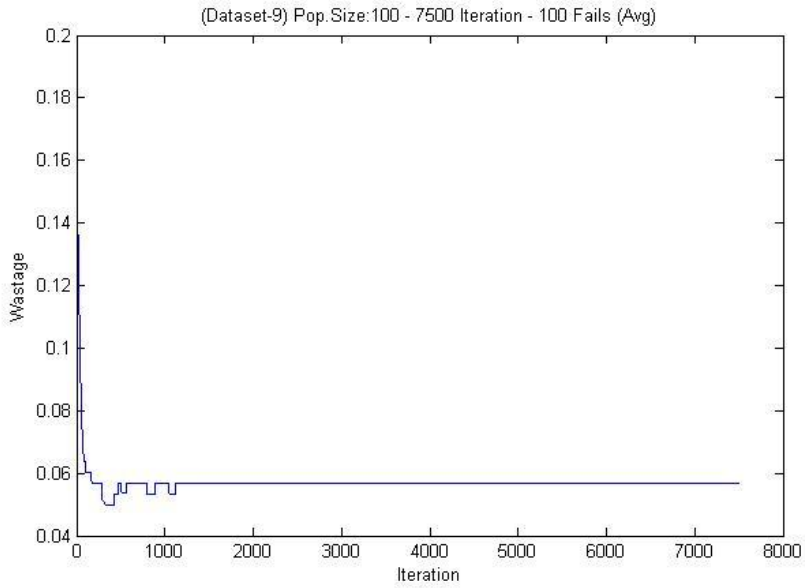

Fig. 33.B: Average Wastage for Table 15.C

Table 15.D: Results of Classic ABC Algorithm for Itemset-7 Group-11

Swarm:100 Iteration:7500 Max Number of Fail:100 Minimum Bin Usage Ratio:0.50 Group:11 Optimum Number of Bin:83																		
Test	1		2		3		4		5		OVERALL							
Time(sc)	2.11E+03		2.02E+03		2.06E+03		2.09E+03		2.14E+03		BIN				WASTE			
	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Best	No.Best	Mean	St. Dev.	Best	No.Best	Mean	St. Dev.
Best	87	0.0492	88	0.0568	88	0.0571	88	0.0531	88	0.0509	87	1	87.8	0.4472	0.0492	1	0.0534	0.0035
Mean	88.027	0.0573	88.059	0.0575	88.05	0.0585	88.058	0.0579	88.057	0.0581	88.027	1	88.050	0.0136	0.0573	1	0.0578	0.0005
St. Dev.	0.6528	0.0064	0.6222	0.0063	0.6222	0.0063	0.6792	0.0070	0.6542	0.0060	0.6222	2	0.6461	0.0242	0.0060	1	0.0064	0.0004

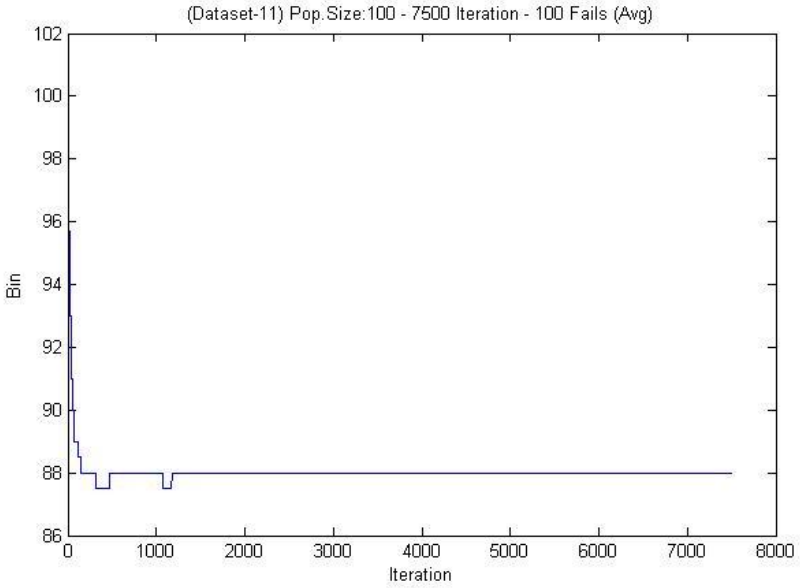

Fig. 34.A: Average Number of Bin for Table 15.D

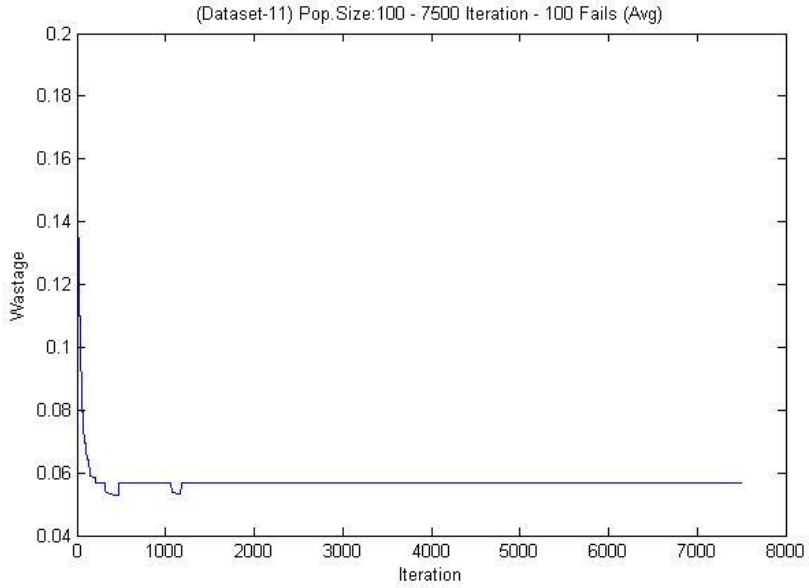

Fig. 34.B: Average Wastage for Table 15.D

Table 15.E: Results of Classic ABC Algorithm for Itemset-7 Group-15

Swarm:100 Iteration:7500 Max Number of Fail:100 Minimum Bin Usage Ratio:0.50 Group:15 Optimum Number of Bin:83																		
Test	1		2		3		4		5		OVERALL							
Time(sc)	2.00E+03		2.03E+03		2.05E+03		2.09E+03		2.01E+03		BIN				WASTE			
	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Best	No.Best	Mean	St. Dev.	Best	No.Best	Mean	St. Dev.
Best	87	0.0491	87	0.0496	87	0.0495	87	0.0506	87	0.0491	87	5	87	0.0000	0.0491	1	0.0496	0.0006
Mean	87.974	0.0568	87.969	0.0568	87.851	0.0574	87.969	0.0538	87.92	0.0556	87.851	1	87.937	0.0526	0.0538	1	0.0561	0.0014
St. Dev.	0.6503	0.0062	0.6289	0.0060	0.6371	0.0064	0.6379	0.0058	0.6187	0.0068	0.6187	1	0.6346	0.0117	0.0058	1	0.0062	0.0004

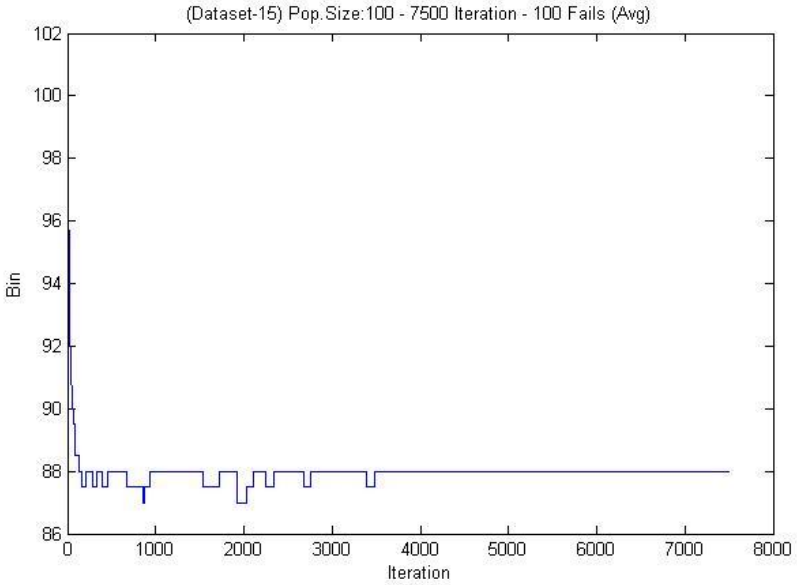

Fig. 35.A: Average Number of Bin for Table 15.E

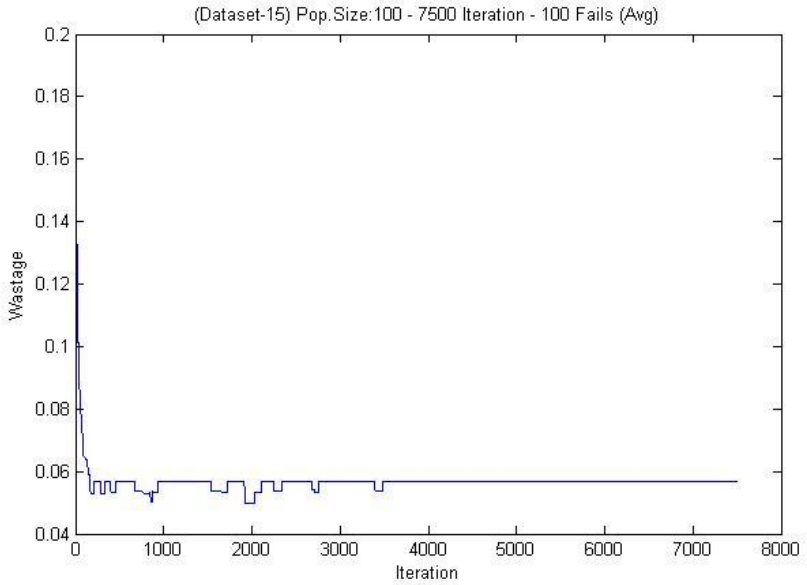

Fig. 35.B: Average Wastage for Table 15.E

Table 16: Results of Classic ABC Algorithm and MEABC Algorithm for Itemset-8

			BIN	WASTAGE	TIME
ABC	DS8	100-7500-100	175	0.0473	6.1104e+03
MEABC	DS8	100-7500-100-1500	176	0.0528	5.9364e+03
ABC	DS10	100-7500-100	175	0.0478	5.9984e+03
MEABC	DS10	100-7500-100-1500	176	0.0511	5.8629e+03
ABC	DS13	100-7500-100	176	0.0529	6.1680e+03
MEABC	DS13	100-7500-100-1500	176	0.0529	5.9892e+03
ABC	DS16	100-7500-100	176	0.0531	5.2290e+03
MEABC	DS16	100-7500-100-1500	176	0.0530	5.9002e+03
ABC	DS19	100-7500-100	177	0.0565	5.8586e+03
MEABC	DS19	100-7500-100-1500	176	0.0511	5.9576e+03

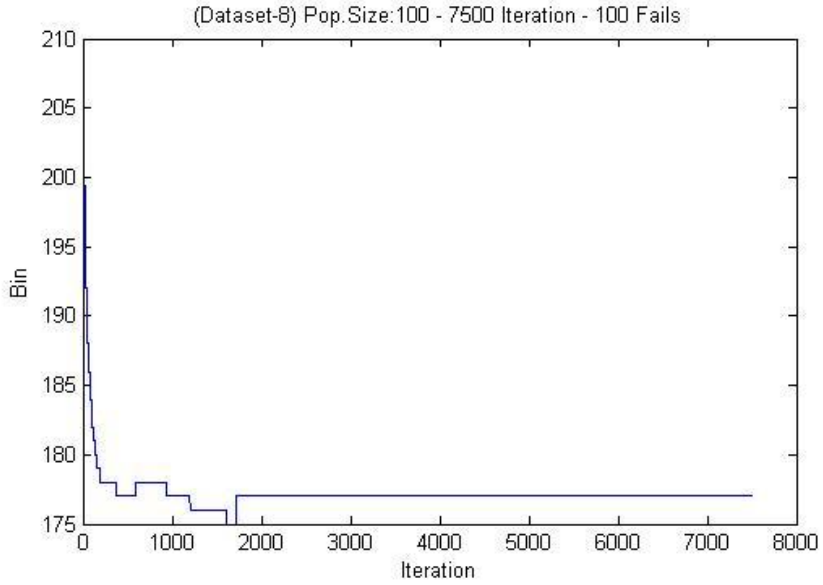

Fig. 36.A: ABC Results for Number of Bin for Group-8 in Table 16

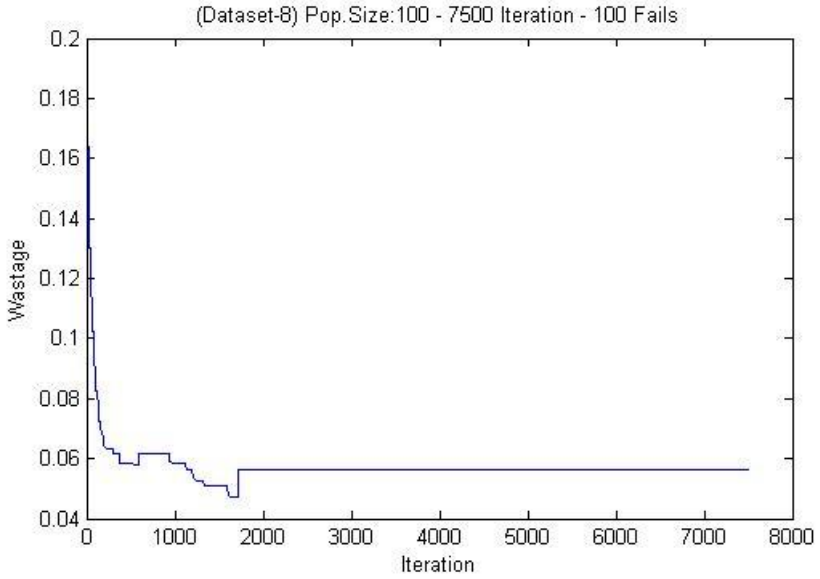

Fig. 36.B: ABC Results for Wastage for Group-8 in Table 16

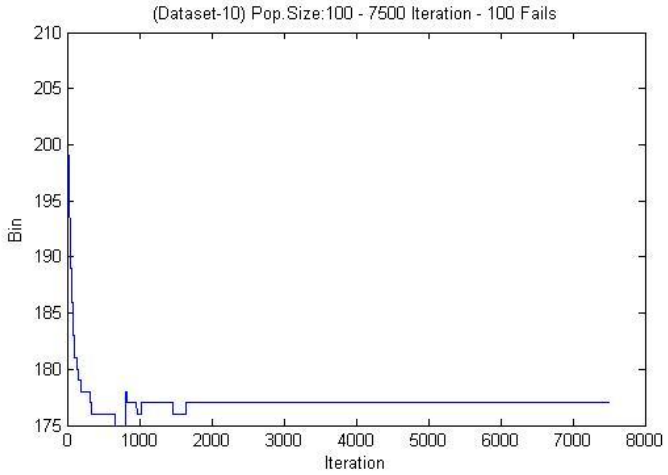

Fig. 37.A: ABC Results for Number of Bin for Group-10 in Table 16

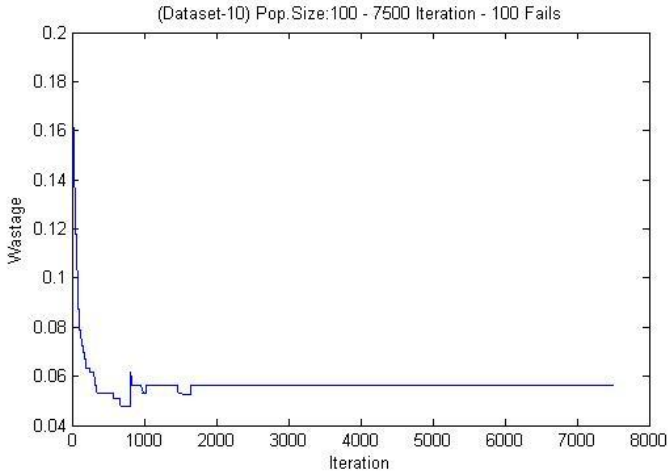

Fig. 37.B: ABC Results for Wastage for Group-10 in Table 16

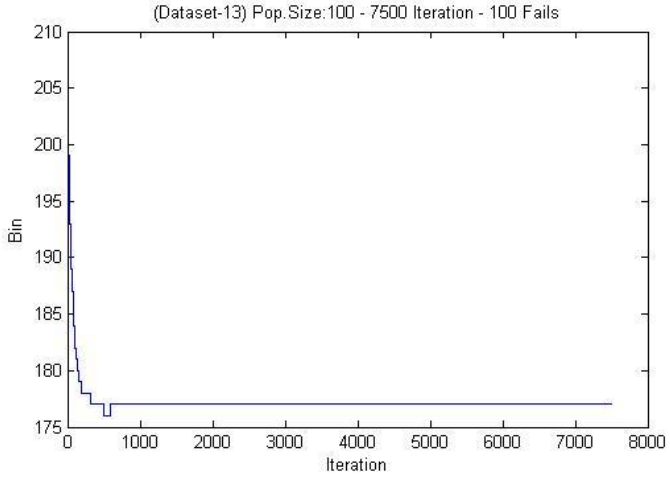

Fig. 38.A: ABC Results for Number of Bin for Group-13 in Table 16

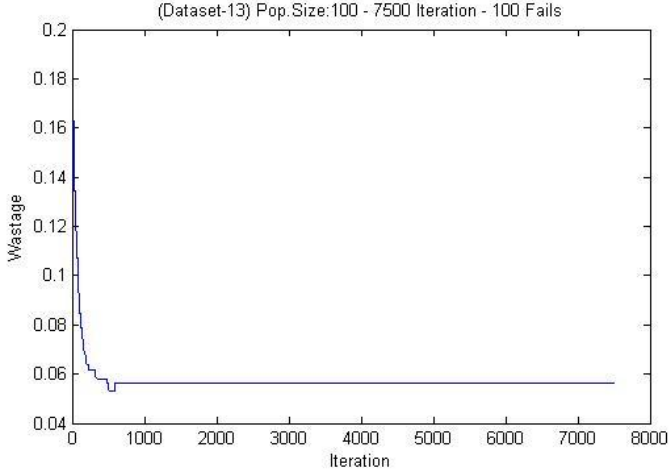

Fig. 38.B: ABC Results for Wastage for Group-13 in Table 16

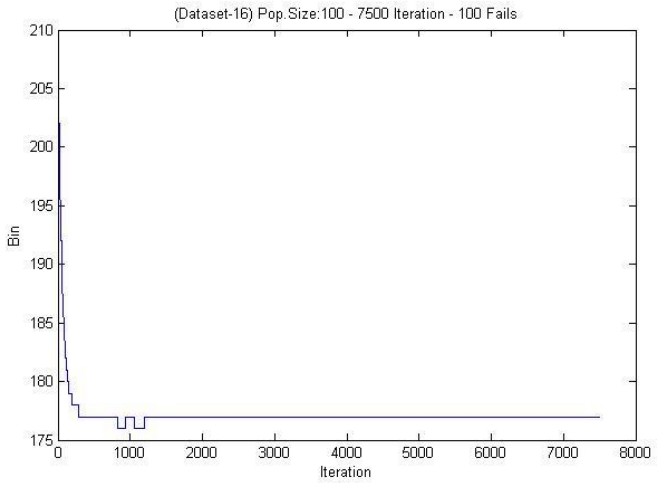

Fig. 39.A: ABC Results for Number of Bin for Group-16 in Table 16

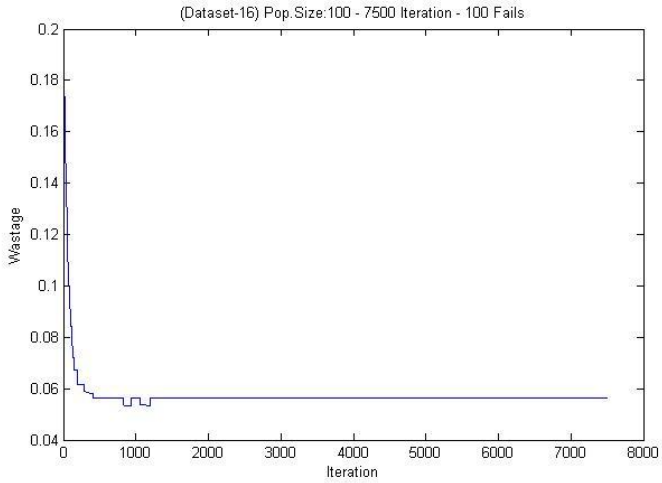

Fig. 39.B: ABC Results for Wastage for Group-16 in Table 16

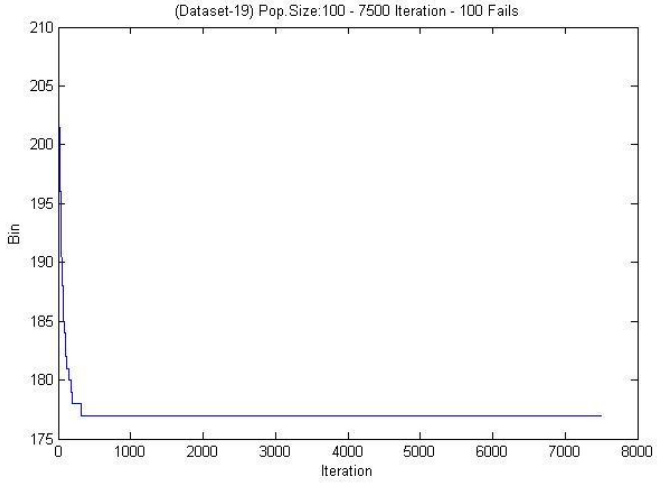

Fig. 40.A: ABC Results for Number of Bin for Group-19 in Table 16

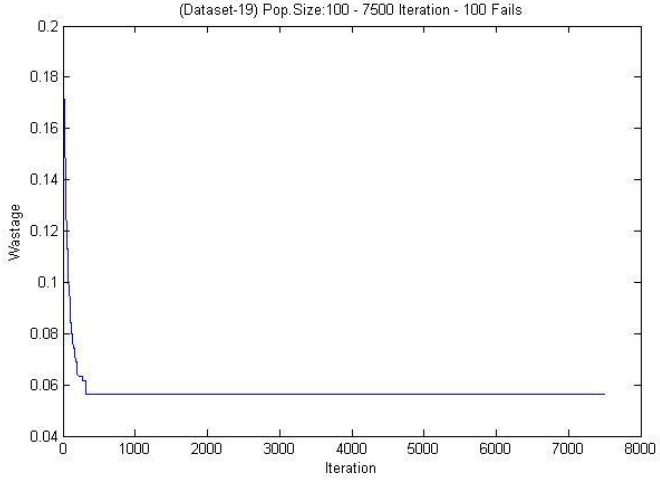

Fig. 40.B: ABC Results for Wastage for Group-19 in Table 16

Appendix C

Table-17.A: Results of MEABC Algorithm for Itemset-1 Group-1

Swarm:100 Iteration:7500 Max Number of Fail:100 Tabu Period:1500 Minimum Bin Usage Ratio:0.50 Group:1 Optimum Number of Bin:48																		
Test	1		2		3		4		5		OVERALL							
Time(sc)	958.1862		957.146		965.2645		954.3279		975.3468		BIN				WASTE			
	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Best	No.Best	Mean	St. Dev.	Best	No.Best	Mean	St. Dev.
Best	48	0.0226	48	0.0228	49	0.037	48	0.0229	48	0.0228	48	4	48.2	0.4472	0.0226	1	0.0256	0.0064
Mean	48.946	0.0366	48.987	0.0372	49.038	0.0379	48.946	0.0369	48.987	0.0372	48.946	1	48.981	0.0381	0.0366	1	0.0372	0.0005
St. Dev.	0.4886	0.0083	0.4639	0.008	0.3392	0.0064	0.4886	0.0083	0.4639	0.008	0.3392	1	0.4488	0.0625	0.0064	1	0.0078	0.0008

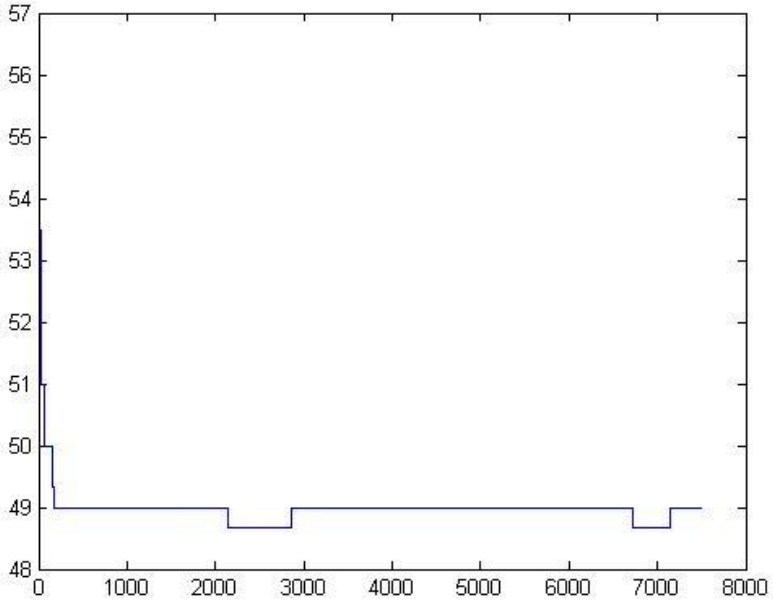

Fig. 41.A: Average Number of Bin for Table 17.A

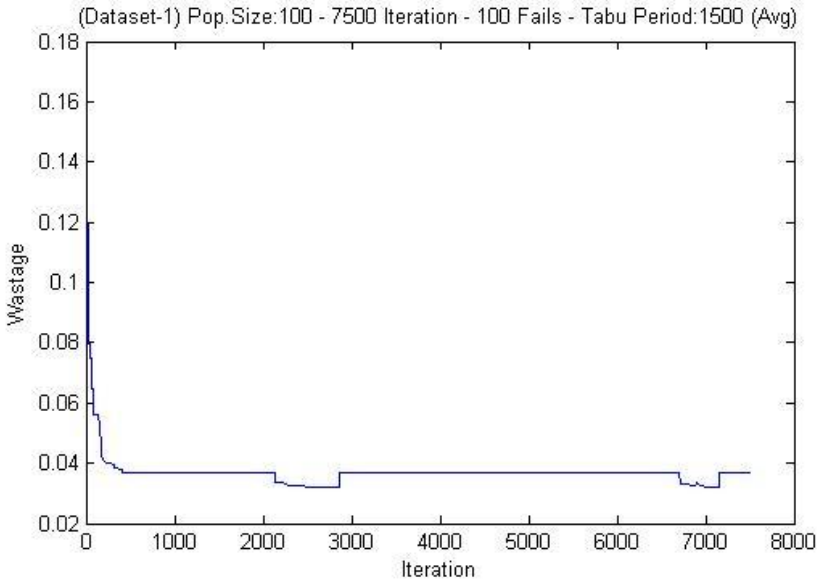

Fig. 41.B: Average Wastage for Table 17.A

Table-17.B: Results of MEABC Algorithm for Itemset-1 Group-7

Swarm:100 Iteration:7500 Max Number of Fail:100 Tabu Period:1500 Minimum Bin Usage Ratio:0.50 Group:7 Optimum Number of Bin:48																		
Test	1		2		3		4		5		OVERALL							
Time(sc)	936.2807		940.6256		972.808		968.3975		955.5571		BIN				WASTE			
	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Best	No.Best	Mean	St. Dev.	Best	No.Best	Mean	St. Dev.
Best	49	0.029	49	0.029	49	0.029	49	0.029	49	0.029	49	5	49	0.0000	0.0290	5	0.0290	0.0000
Mean	49.058	0.0302	49.054	0.0303	49.04	0.0298	49.058	0.0301	49.054	0.0308	49.040	1	49.053	0.0075	0.0298	1	0.0302	0.0004
St. Dev.	0.4355	0.0081	0.4078	0.0077	0.3795	0.0071	0.4355	0.0081	0.4078	0.0077	0.3795	1	0.4132	0.0234	0.0071	1	0.0077	0.0004

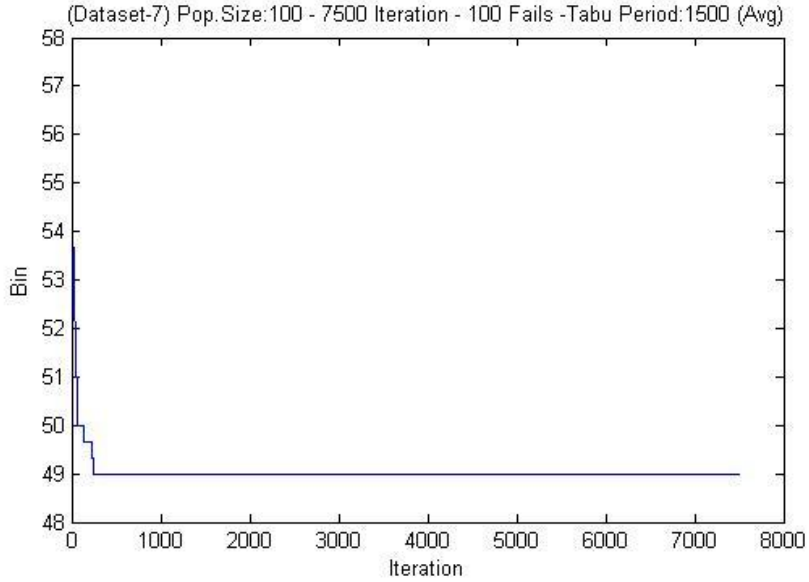

Fig. 42.A: Average Number of Bin for Table 17.B

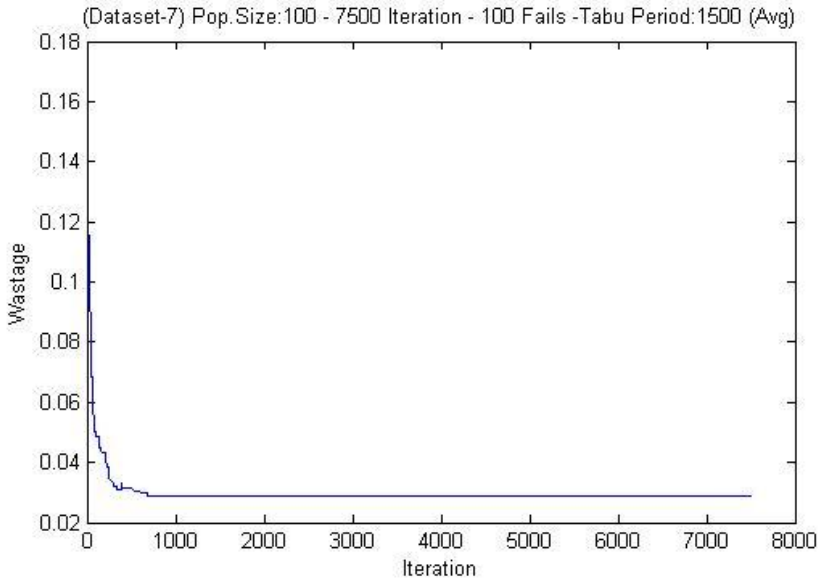

Fig. 42.B: Average Wastage for Table 17.B

Table-17.C: Results of MEABC Algorithm for Itemset-1 Group-8

Swarm:100 Iteration:7500 Max Number of Fail:100 Tabu Period:1500 Minimum Bin Usage Ratio:0.50 Group:8 Optimum Number of Bin:49																			
Test	1		2		3		4		5		OVERALL								
Time(sc)	985.1429		996.7917		986.5185		998.3497		981.2349		BIN				WASTE				
	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Best	No.Best	Mean	St. Dev.	Best	No.Best	Mean	St. Dev.
Best	50	0.0273	50	0.0273	50	0.0273	50	0.0273	50	0.0273	50	5	50	0.0000	0.0273	5	0.0273	0.0000
Mean	50.07	0.029	50.046	0.0284	50.04	0.0283	50.069	0.0291	50.046	0.0286	50.040	1	50.054	0.0139	0.0283	1	0.0287	0.0004
St. Dev.	0.3716	0.007	0.3527	0.0068	0.3402	0.0065	0.3716	0.007	0.3527	0.0068	0.3402	1	0.3578	0.0136	0.0065	1	0.0068	0.0002

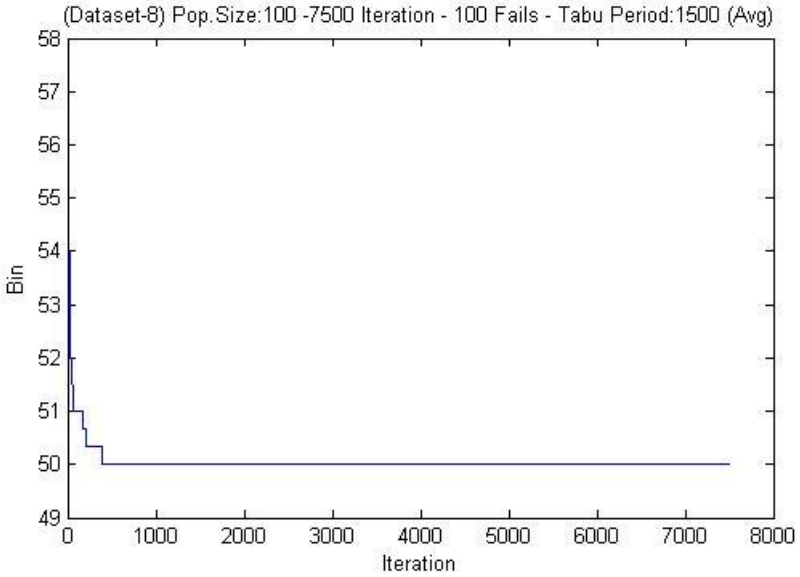

Fig. 43.A: Average Number of Bin for Table 17.C

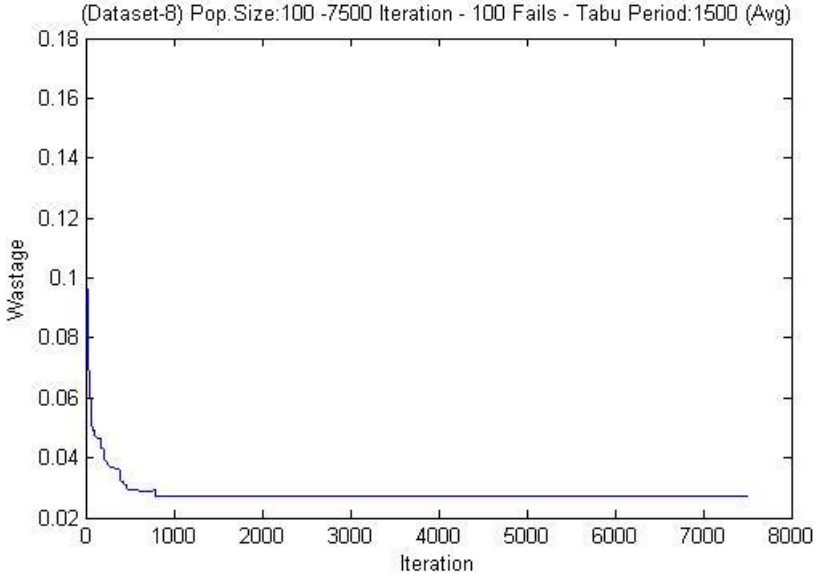

Fig. 43.B: Average Wastage for Table 17.C

Table-17.D: Results of MEABC Algorithm for Itemset-1 Group-12

Swarm:100 Iteration:7500 Max Number of Fail:100 Tabu Period:1500 Minimum Bin Usage Ratio:0.50 Group:12 Optimum Number of Bin:49																			
Test	1		2		3		4		5		OVERALL								
Time(sc)	990.0229		977.3885		972.2788		987.3689		976.5284		BIN				WASTE				
	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Best	No.Best	Mean	St. Dev.	Best	No.Best	Mean	St. Dev.
Best	50	0.0337	50	0.0337	50	0.0337	50	0.0337	50	0.0337	50	5	50	0.0000	0.0337	5	0.0337	0.0000
Mean	50.064	0.035	50.064	0.0351	50.068	0.0351	50.065	0.035	50.064	0.0351	50.064	1	50.065	0.0018	0.0350	2	0.0351	0.0001
St. Dev.	0.4863	0.0087	0.5065	0.0091	0.4801	0.0087	0.4863	0.0087	0.5065	0.0091	0.4801	1	0.4931	0.0125	0.0087	3	0.0089	0.0002

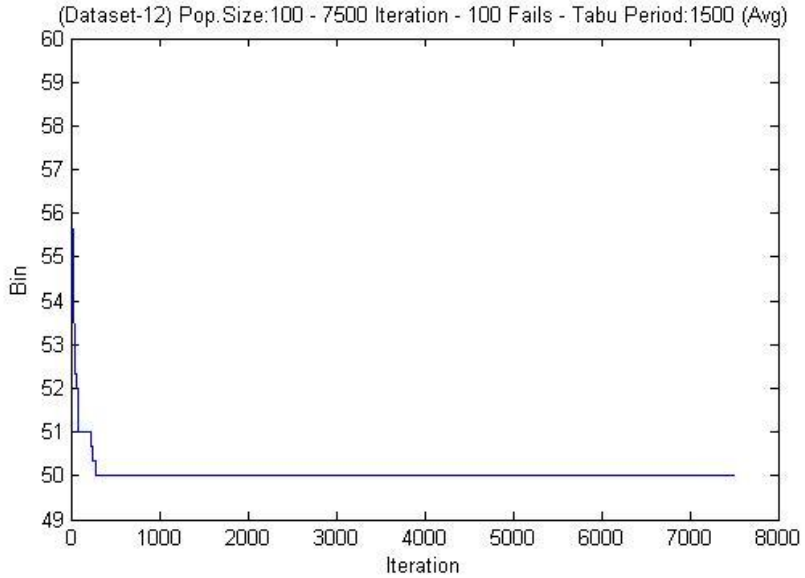

Fig. 44.A: Average Number of Bin for Table 17.D

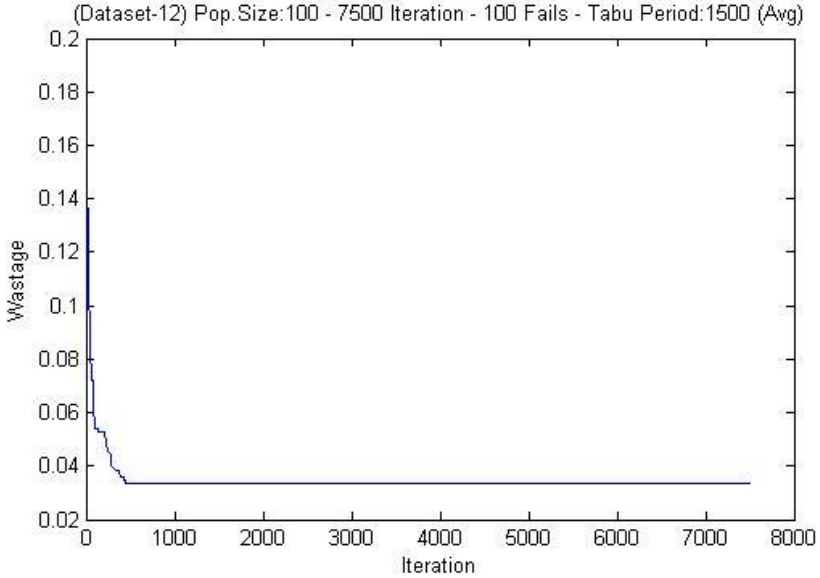

Fig. 44.B: Average Wastage for Table 17.D

Table-17.E: Results of MEABC Algorithm for Itemset-1 Group-17

Swarm:100 Iteration:7500 Max Number of Fail:100 Tabu Period:1500 Minimum Bin Usage Ratio:0.50 Group:17 Optimum Number of Bin:52																		
Test	1		2		3		4		5		OVERALL							
Time(sc)	1.01E+03		1.00E+03		9.96E+02		972.2788		990.0229		BIN				WASTE			
	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Best	No.Best	Mean	St. Dev.	Best	No.Best	Mean	St. Dev.
Best	53	0.033	52	0.0222	53	0.033	53	0.033	53	0.033	52	1	52.8	0.4472	0.0222	1	0.0308	0.0048
Mean	53.059	0.0341	53.048	0.0339	53.057	0.0341	53.059	0.0341	53.059	0.0341	53.048	1	53.056	0.0049	0.0339	1	0.0341	0.0001
St. Dev.	0.525	0.0089	0.5436	0.009	0.4706	0.0081	0.525	0.0089	0.525	0.0089	0.4706	1	0.5178	0.0276	0.0081	1	0.0088	0.0004

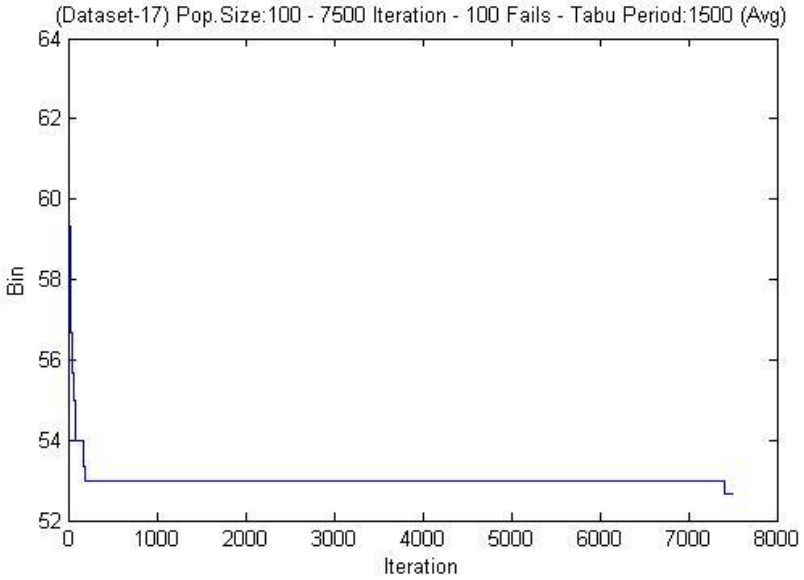

Fig. 45.A: Average Number of Bin for Table 17.E

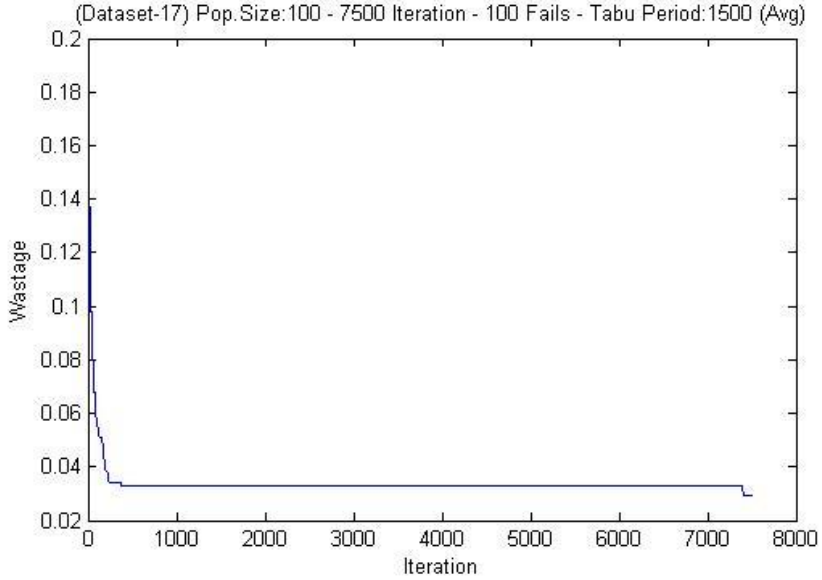

Fig. 45.B: Average Wastage for Table 17.E

Table-18.A: Results of MEABC Algorithm for Itemset-2 Group-5

Swarm:100 Iteration:7500 Max Number of Fail:100 Tabu Period:1500 Minimum Bin Usage Ratio:0.50 Group:5 Optimum Number of Bin:101																		
Test	1		2		3		4		5		OVERALL							
Time(sc)	2.53E+03		2.48E+03		2.51E+03		2.51E+03		2.45E+03		BIN				WASTE			
	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Best	No.Best	Mean	St. Dev.	Best	No.Best	Mean	St. Dev.
Best	103	0.0256	103	0.0249	103	0.0256	103	0.0256	103	0.0256	103	5	103	0.0000	0.0249	1	0.0254	0.0003
Mean	104.11	0.0338	104	0.0332	104.11	0.0338	104.11	0.0338	104.11	0.0338	104	1	104.09	0.0494	0.0332	1	0.0337	0.0003
St. Dev.	1.3931	0.0115	1.4807	0.0123	1.3931	0.0115	1.3931	0.0115	1.3931	0.0115	1.3931	4	1.4106	0.0392	0.0115	4	0.0117	0.0003

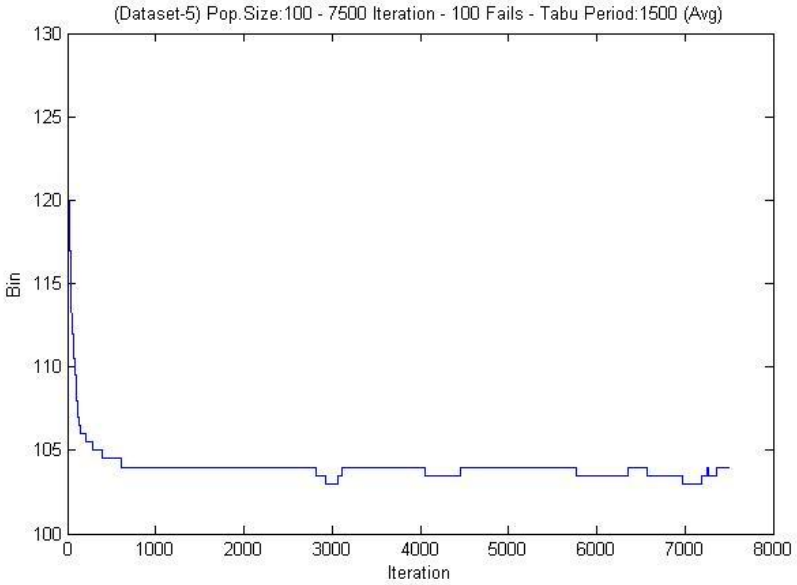

Fig. 46.A: Average Number of Bin for Table 18.A

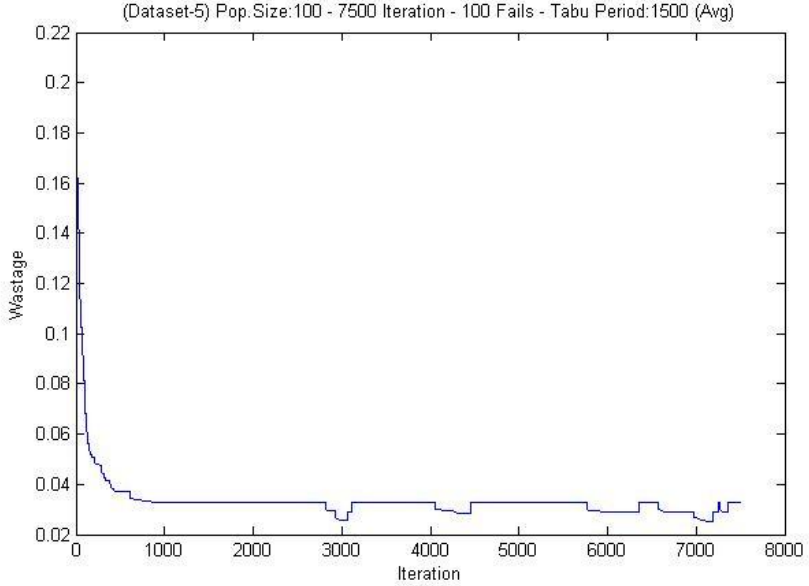

Fig. 46.B: Average Wastage for Table 18.A

Table-18.B: Results of MEABC Algorithm for Itemset-2 Group-6

Swarm:100 Iteration:7500 Max Number of Fail:100 Tabu Period:1500 Minimum Bin Usage Ratio:0.50 Group:6 Optimum Number of Bin:101																		
Test	1		2		3		4		5		OVERALL							
Time(sc)	2.39E+03		2.95E+03		2.29E+03		2.78E+03		2.57E+03		BIN				WASTE			
	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Best	No.Best	Mean	St. Dev.	Best	No.Best	Mean	St. Dev.
Best	104	0.0305	104	0.0305	104	0.0305	104	0.0305	104	0.0305	104	5	104	0.0000	0.0305	5	0.0305	0.0000
Mean	104.34	0.0340	104.36	0.0338	104.34	0.0340	104.34	0.0340	104.34	0.0340	104.340	1	104.346	0.0097	0.0338	1	0.0340	0.0001
St. Dev.	1.4897	0.0125	1.5976	0.0134	1.4897	0.0125	1.4897	0.0125	1.4897	0.0125	1.4897	4	1.5113	0.0482	0.0125	4	0.0127	0.0004

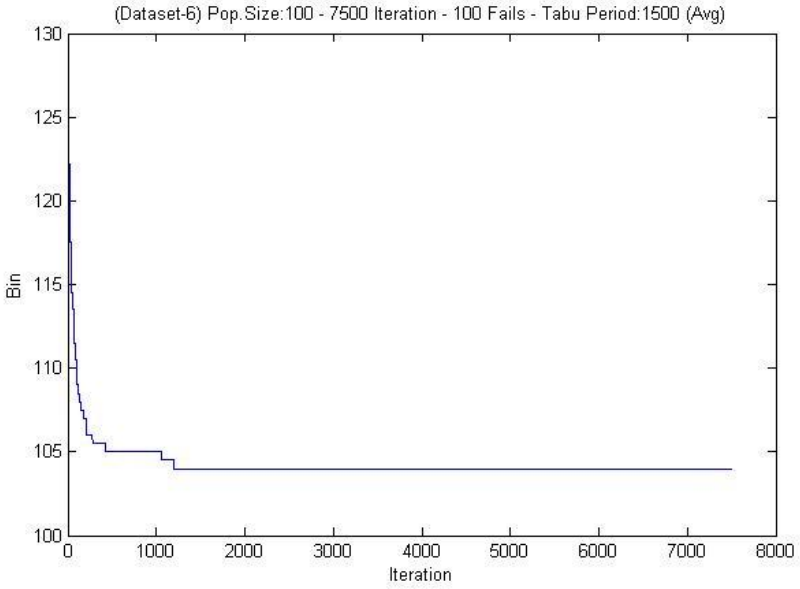

Fig. 47.A: Average Number of Bin for Table 18.B

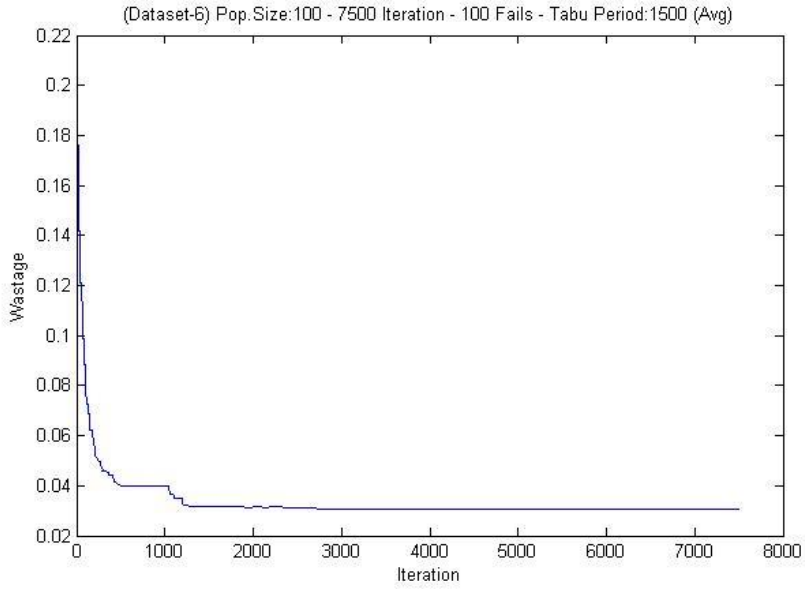

Fig. 47.B: Average Wastage for Table 18.B

Table-18.C: Results of MEABC Algorithm for Itemset-2 Group-14

Swarm:100 Iteration:7500 Max Number of Fail:100 Tabu Period:1500 Minimum Bin Usage Ratio:0.50 Group:14 Optimum Number of Bin:103																		
Test	1		2		3		4		5		OVERALL							
Time(sc)	2.33E+03		2.32E+03		2.32E+03		2.31E+03		2.57E+03		BIN				WASTE			
	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Best	No.Best	Mean	St. Dev.	Best	No.Best	Mean	St. Dev.
Best	105	0.0290	105	0.0290	105	0.0290	105	0.0290	105	0.0290	105	5	105	0.0000	0.0290	5	0.0290	0.0000
Mean	105.99	0.0383	105.45	0.0341	105.68	0.0352	105.99	0.0383	105.68	0.0379	105.452	1	105.759	0.2323	0.0341	1	0.0368	0.0020
St. Dev.	1.4359	0.0117	1.5642	0.0128	1.4682	0.0124	1.4359	0.0117	1.4682	0.0124	1.4359	2	1.4744	0.0527	0.0117	2	0.0122	0.0005

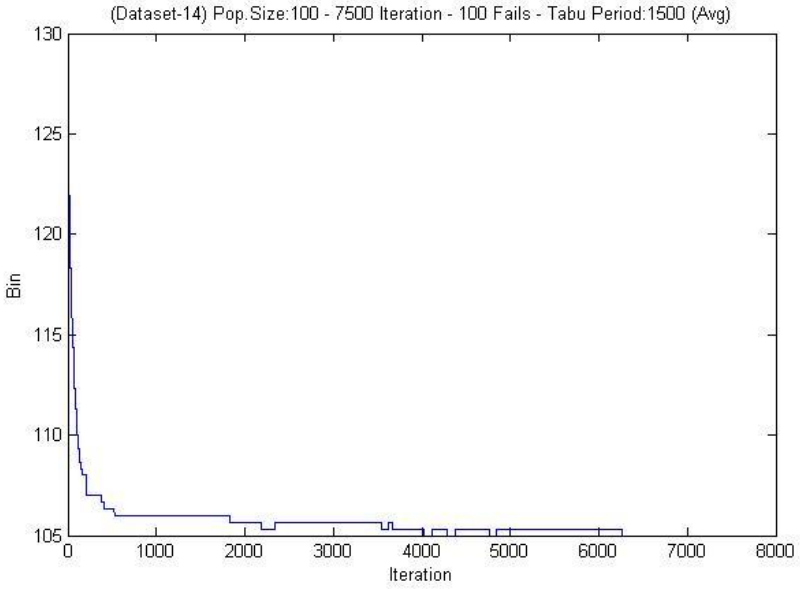

Fig. 48.A: Average Number of Bin for Table 18.C

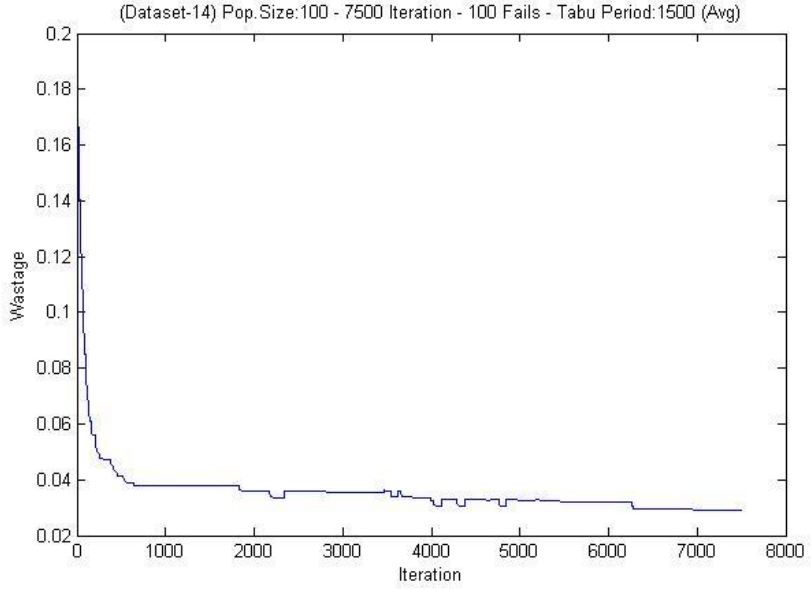

Fig. 48.B: Average Wastage for Table 18.C

Table-18.D: Results of MEABC Algorithm for Itemset-2 Group-16

Swarm:100 Iteration:7500 Max Number of Fail:100 Tabu Period:1500 Minimum Bin Usage Ratio:0.50 Group:16 Optimum Number of Bin:105																		
Test	1		2		3		4		5		OVERALL							
Time(sc)	2.12E+03		2.12E+03		2.13E+03		2.12E+03		2.35E+03		BIN				WASTE			
	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Best	No.Best	Mean	St. Dev.	Best	No.Best	Mean	St. Dev.
Best	108	0.0295	108	0.0295	108	0.0295	108	0.0295	108	0.0295	108	5	108	0.0000	0.0295	5	0.0295	0.0000
Mean	108.31	0.0323	108.34	0.0326	108.34	0.0356	108.34	0.0326	108.34	0.0326	108.306	1	108.333	0.0154	0.0323	1	0.0331	0.0014
St. Dev.	1.6077	0.0131	1.7157	0.0138	1.7247	0.0138	1.7197	0.0138	1.7188	0.0138	1.6077	1.0000	1.6973	0.0502	0.0131	1.0000	0.0137	0.0003

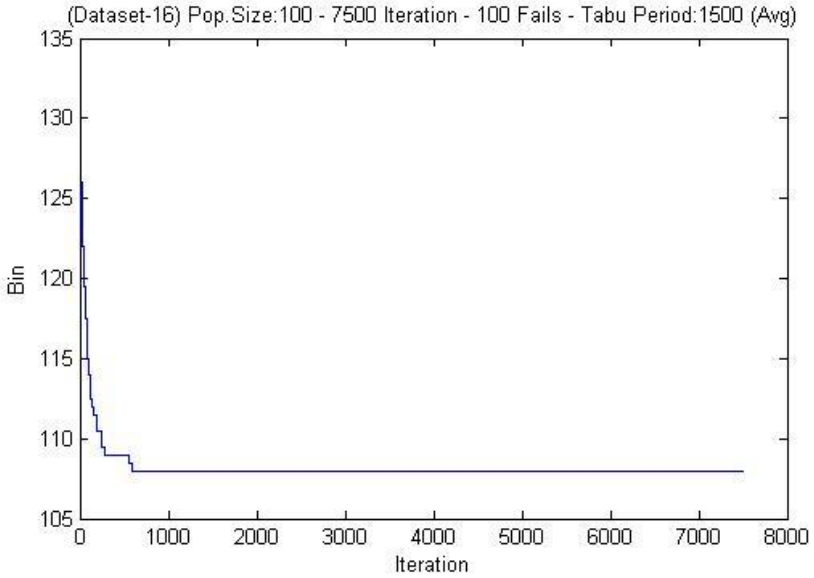

Fig. 49.A: Average Number of Bin for Table 18.D

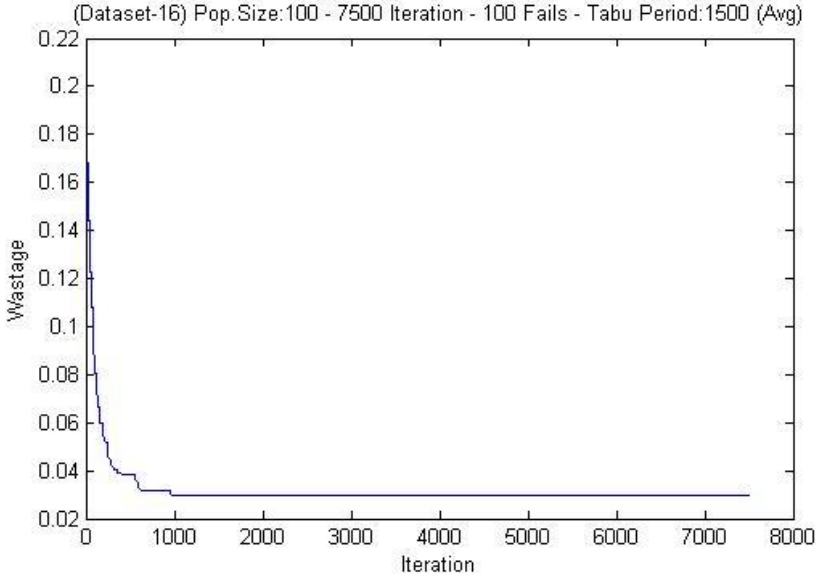

Fig. 49.B: Average Wastage for Table 18.D

Table-18.E: Results of MEABC Algorithm for Itemset-2 Group-19

Swarm:100 Iteration:7500 Max Number of Fail:100 Tabu Period:1500 Minimum Bin Usage Ratio:0.50 Group:19 Optimum Number of Bin:100																		
Test	1		2		3		4		5		OVERALL							
Time(sc)	2.41E+03		2.41E+03		2.49E+03		2.35E+03		2.44E+03		BIN				WASTE			
	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Best	No.Best	Mean	St. Dev.	Best	No.Best	Mean	St. Dev.
Best	102	0.0239	102	0.0244	102	0.0256	102	0.0245	102	0.0242	102	5	102	0.0000	0.0239	1	0.0245	0.0006
Mean	103.14	0.0337	102.95	0.0324	102.99	0.0328	103.01	0.0331	103.13	0.0338	102.949	1	103.043	0.0876	0.0324	1	0.0331	0.0006
St. Dev.	1.4306	0.0122	1.4662	0.0124	1.4306	0.0122	1.4306	0.0122	1.4306	0.0122	1.4306	4	1.4377	0.0159	0.0122	4	0.0122	0.0001

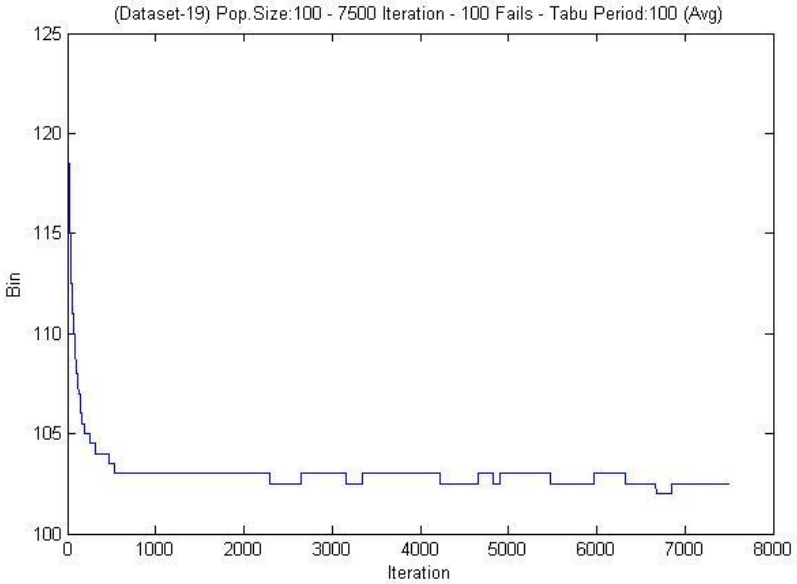

Fig. 50.A: Average Number of Bin for Table 18.E

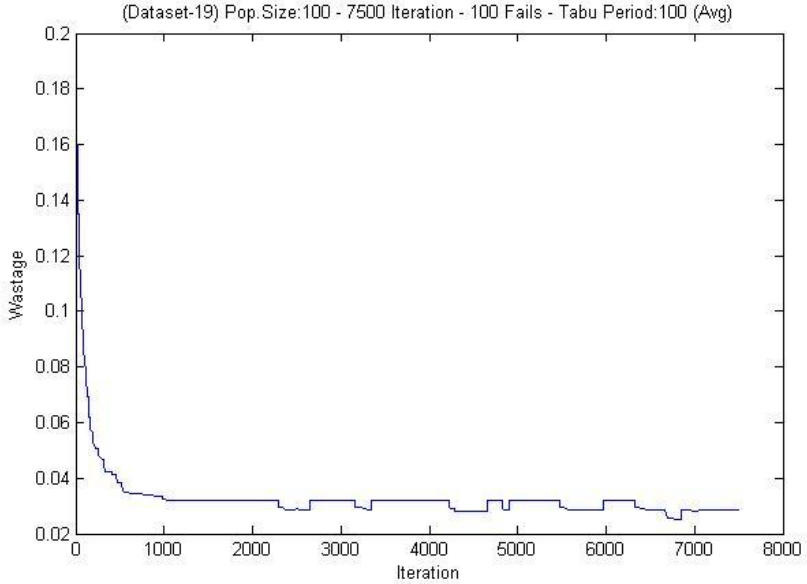

Fig. 50.B: Average Wastage for Table 18.E

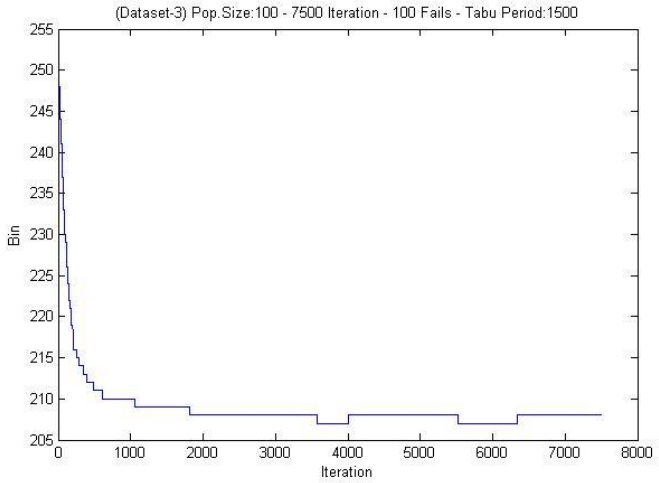

Fig. 51.A: MEABC Results for Number of Bin for Group-3 in Table-11

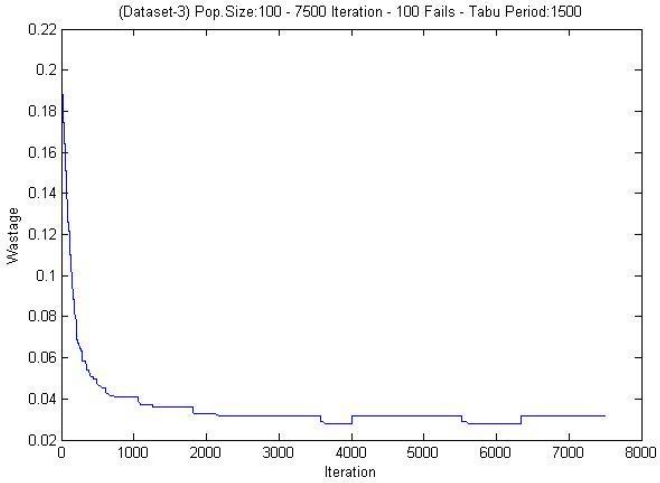

Fig. 51.B: MEABC Results for Wastage for Group-3 in Table-11

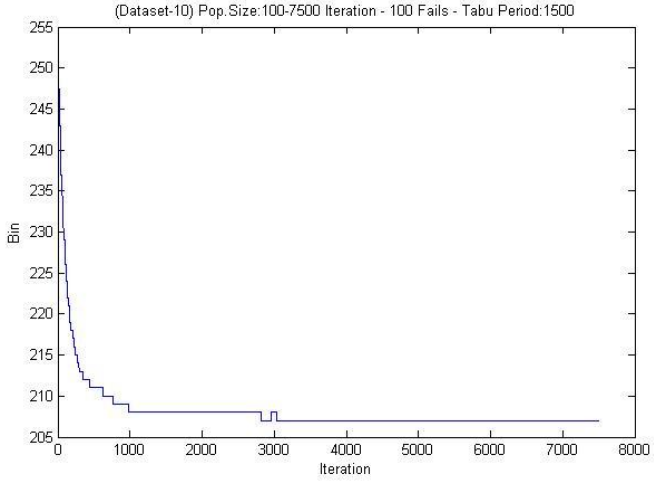

Fig. 52.A: MEABC Results for Number of Bin for Group-10 in Table-11

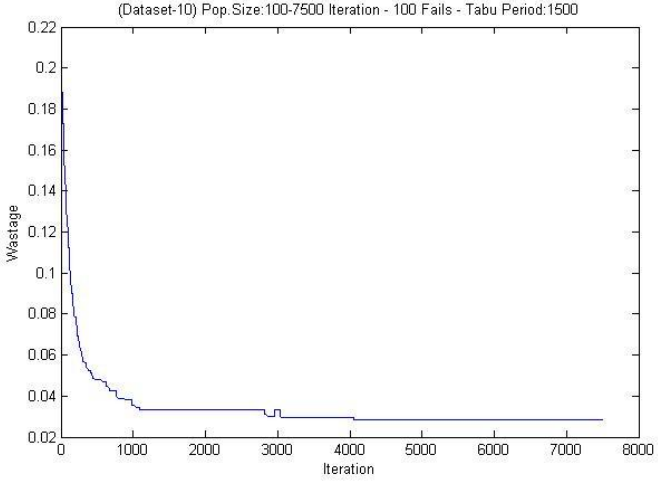

Fig. 52.B: MEABC Results for Wastage for Group-10 in Table-11

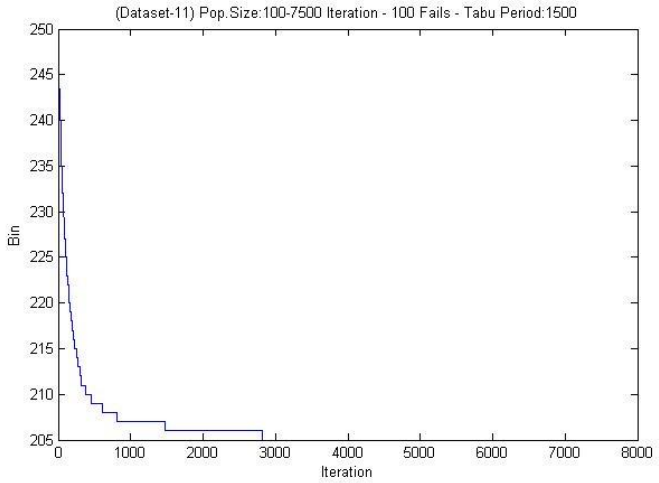

Fig. 53.A: MEABC Results for Number of Bin for Group-11 in Table-11

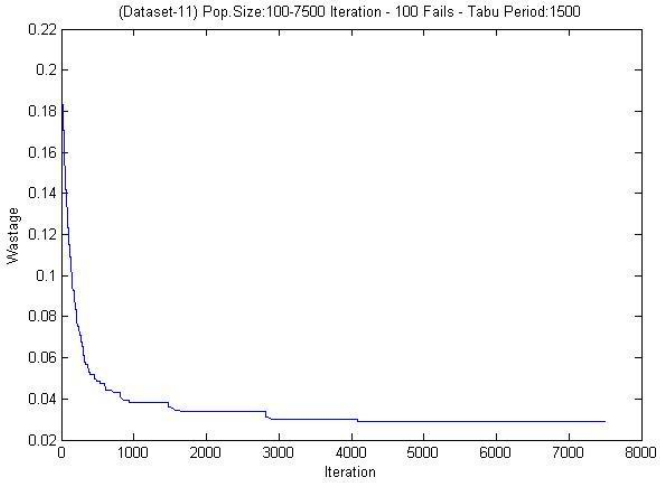

Fig. 53.B: MEABC Results for Wastage for Group-11 in Table-11

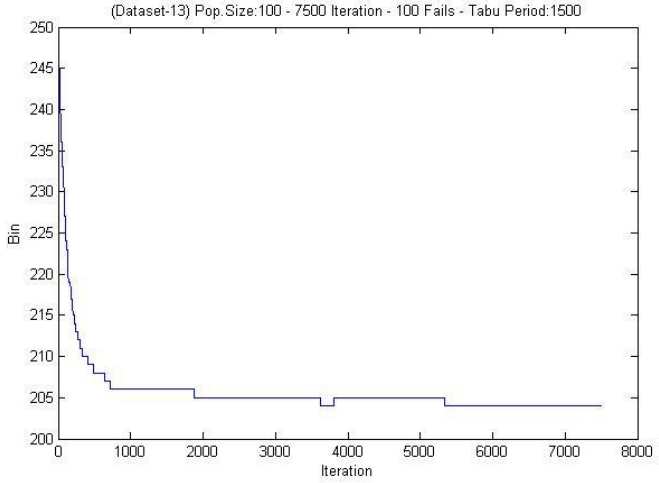

Fig. 54.A: MEABC Results for Number of Bin for Group-13 in Table-11

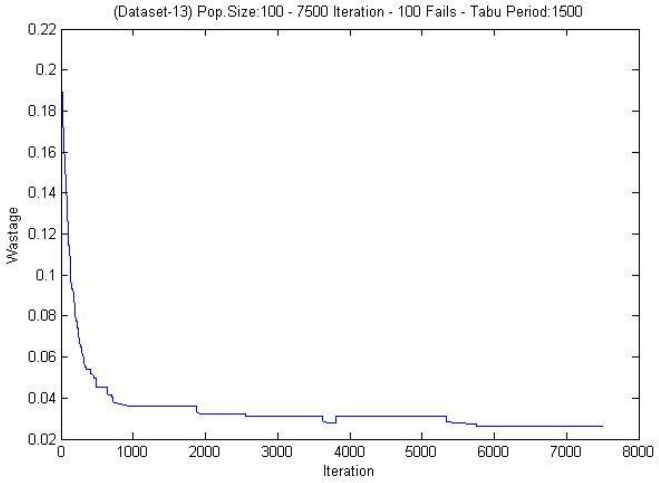

Fig. 54.B: MEABC Results for Wastage for Group-13 in Table-11

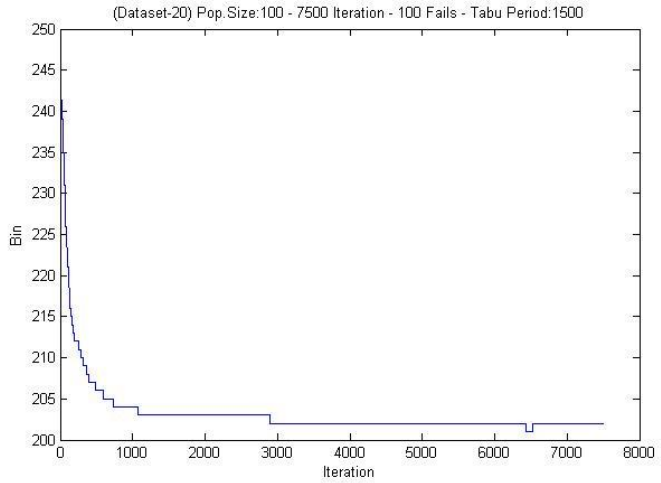

Fig. 55.A: MEABC Results for Number of Bin for Group-20 in Table-11

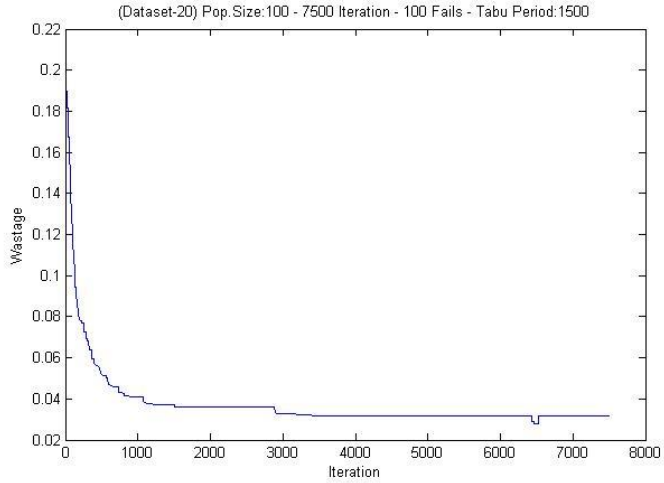

Fig. 55.B: MEABC Results for Wastage for Group-20 in Table-11

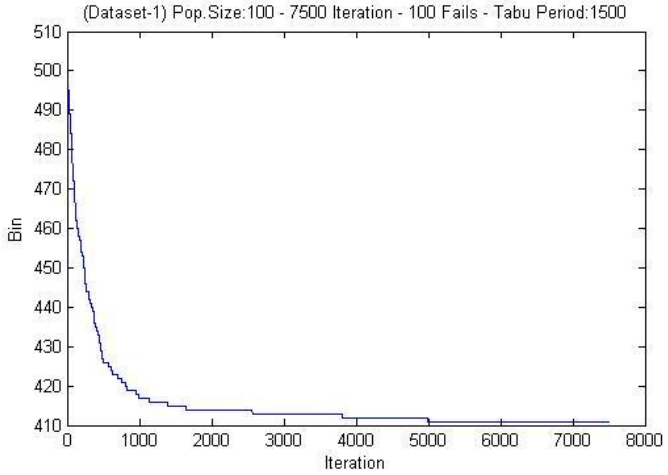

Fig. 56.A: MEABC Results for Number of Bin for Group-1 in Table-12

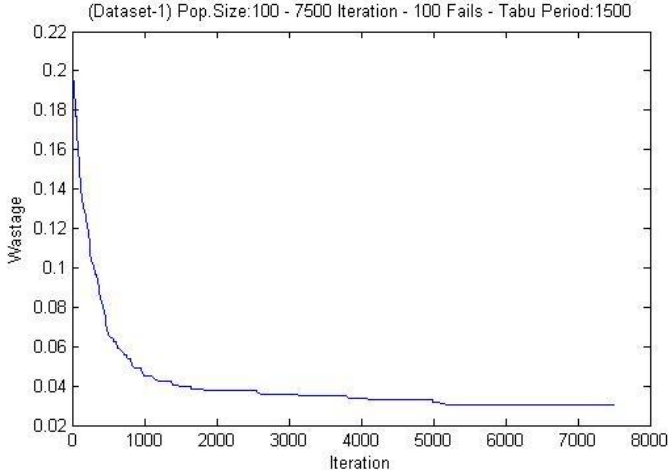

Fig. 56.B: MEABC Results for Wastage for Group-1 in Table-12

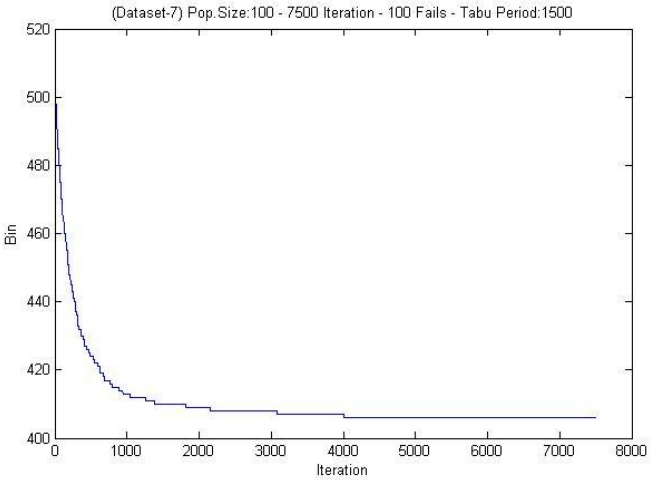

Fig. 57.A: MEABC Results for Number of Bin for Group-7 in Table-12

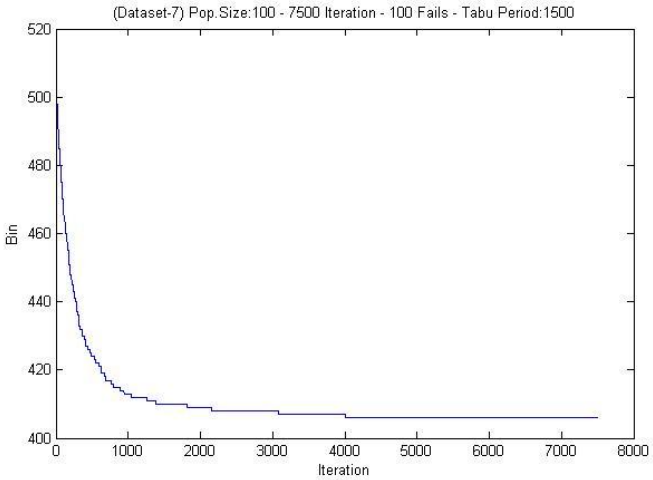

Fig. 57.B: MEABC Results for Wastage for Group-7 in Table-12

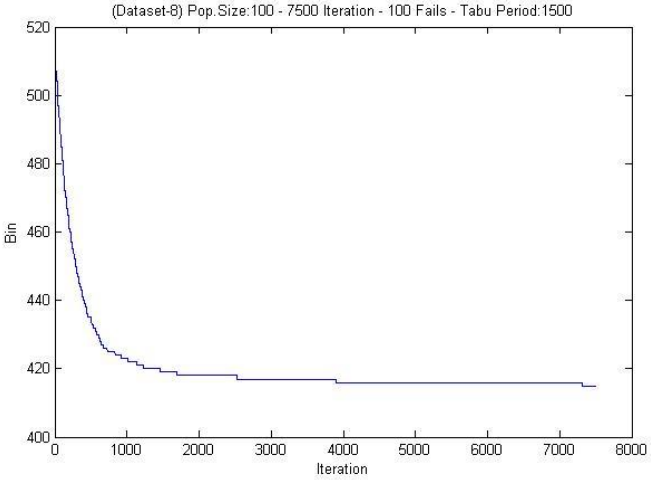

Fig. 58.A: MEABC Results for Number of Bin for Group-8 in Table-12

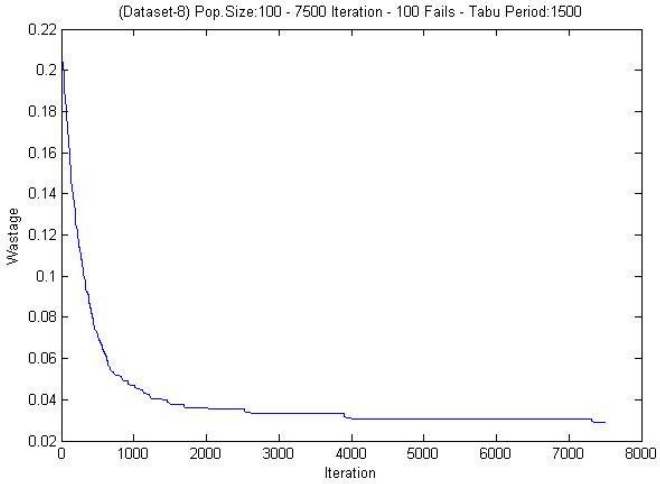

Fig. 58.B: MEABC Results for Wastage for Group-8 in Table-12

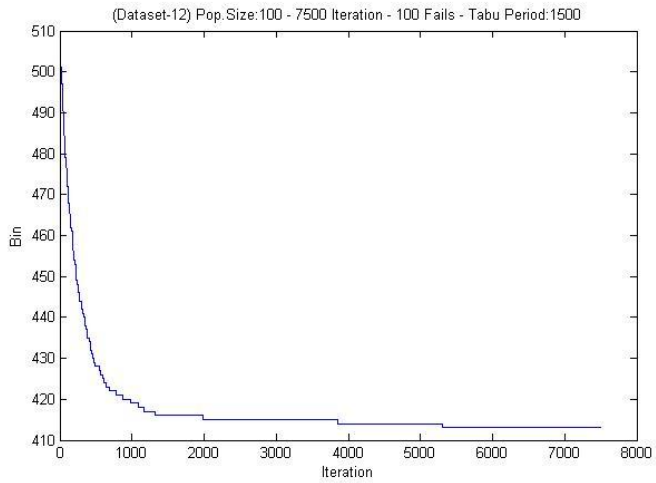

Fig. 59.A: MEABC Results for Number of Bin for Group-12 in Table-12

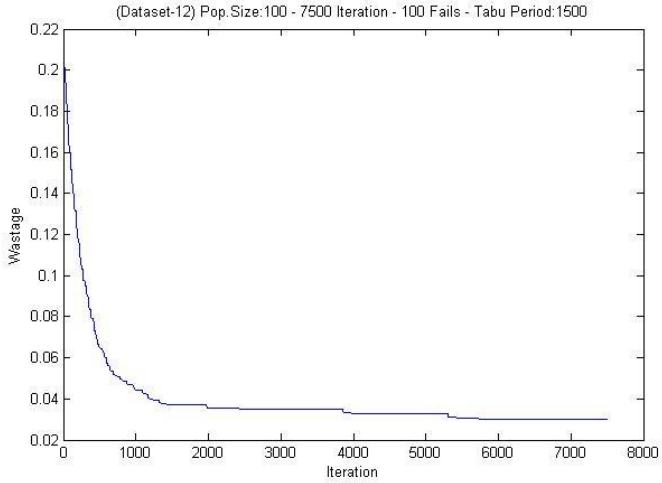

Fig. 59.B: MEABC Results for Wastage for Group-12 in Table-12

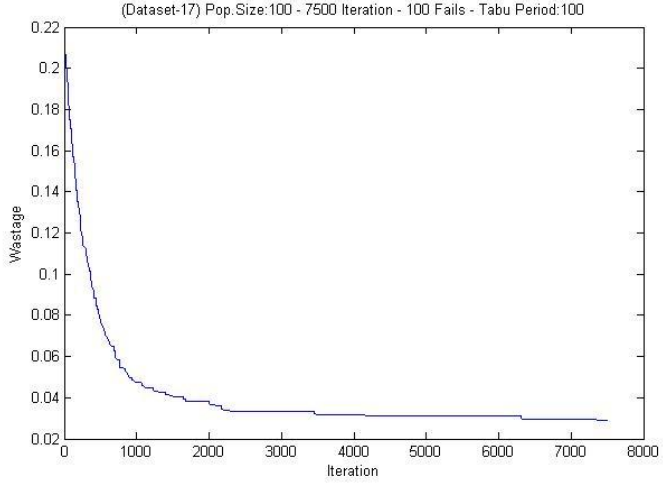

Fig. 60.A: MEABC Results for Number of Bin for Group-17 in Table-12

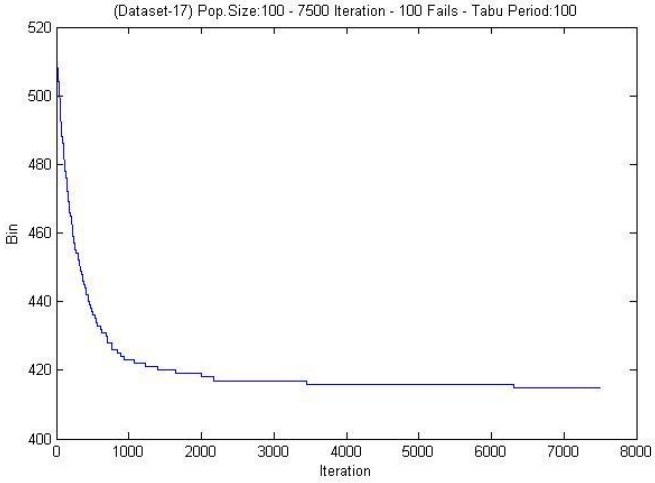

Fig. 60.B: MEABC Results for Wastage for Group-17 in Table-12

Table-19.A: Results of MEABC Algorithm for Itemset-5 Group-2

Swarm:100 Iteration:7500 Max Number of Fail:100 Tabu Period:1500 Minimum Bin Usage Ratio:0.50 Group:2 Optimum Number of Bin:20																			
Test	1		2		3		4		5		OVERALL								
Time(sc)	457.2651		436.4584		456.7254		435.5143		436.4947		BIN				WASTE				
	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Best	No.Best	Mean	St. Dev.	Best	No.Best	Mean	St. Dev.
Best	20	0.0213	21	0.0476	20	0.0232	21	0.0476	20	0.0222	20	3	20.4	0.5477	0.0213	1	0.0324	0.0139
Mean	20.994	0.0476	21.002	0.0478	20.986	0.0473	21.002	0.0477	20.970	0.0469	20.970	1	20.991	0.0132	0.0469	1	0.0475	0.0003
St. Dev.	0.1147	0.0039	0.0490	0.0025	0.1268	0.0034	0.0490	0.0022	0.1756	0.0048	0.0490	1	0.1030	0.0544	0.0022	1	0.0034	0.0010

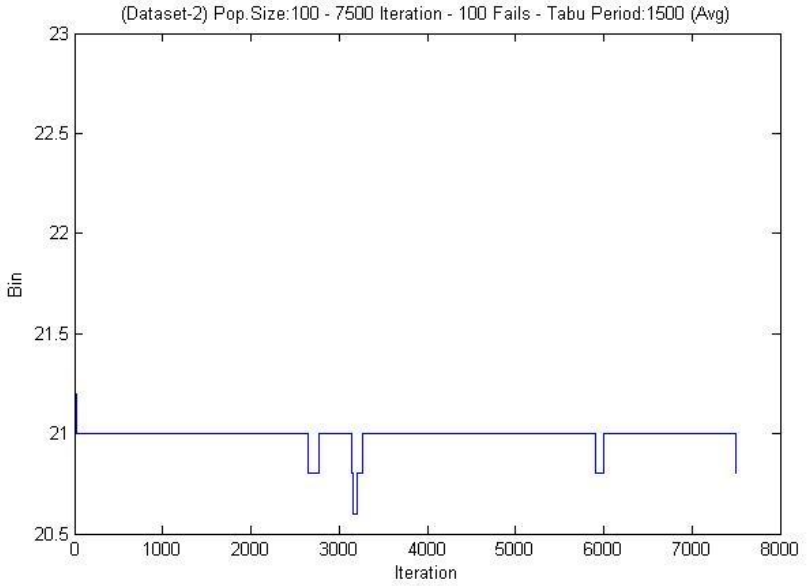

Fig. 61.A: Average Number of Bin for Table 19.A

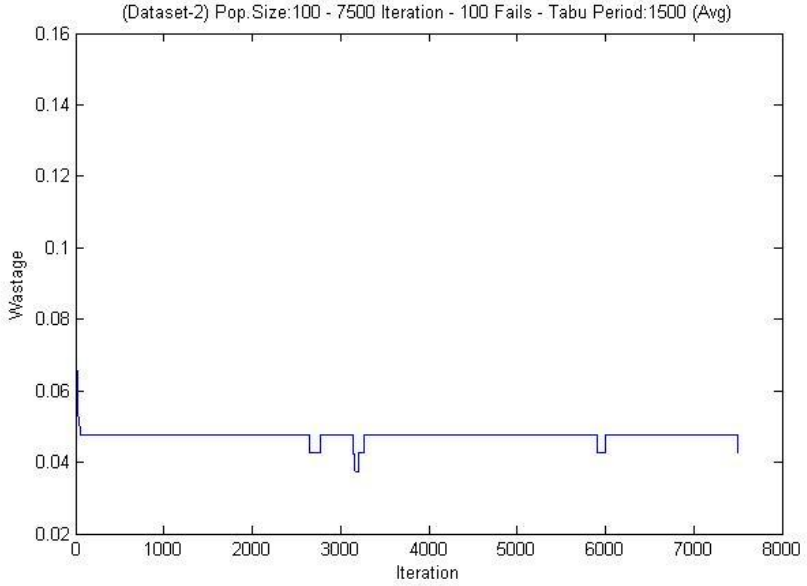

Fig. 61.B: Average Wastage for Table 19.A

Table-19.B: Results of MEABC Algorithm for Itemset-5 Group-4

Swarm:100 Iteration:7500 Max Number of Fail:100 Tabu Period:1500 Minimum Bin Usage Ratio:0.50 Group:4 Optimum Number of Bin:20																		
Test	1		2		3		4		5		OVERALL							
Time(sc)	480.8087		495.2828		494.6943		567.498		486.1935		BIN				WASTE			
	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Best	No.Best	Mean	St. Dev.	Best	No.Best	Mean	St. Dev.
Best	21	0.0476	21	0.0476	21	0.0476	20	0.0195	21	0.0476	20	1	20.8	0.4472	0.0195	1	0.0420	0.0126
Mean	21.003	0.0479	21.003	0.0478	21.003	0.0478	20.982	0.0473	21.003	0.048	20.982	1	20.999	0.0092	0.0473	1	0.0478	0.0003
St. Dev.	0.0599	0.0030	0.0600	0.0028	0.0663	0.0031	0.1477	0.0047	0.0673	0.0035	0.0599	1	0.0802	0.0379	0.0028	1	0.0034	0.0007

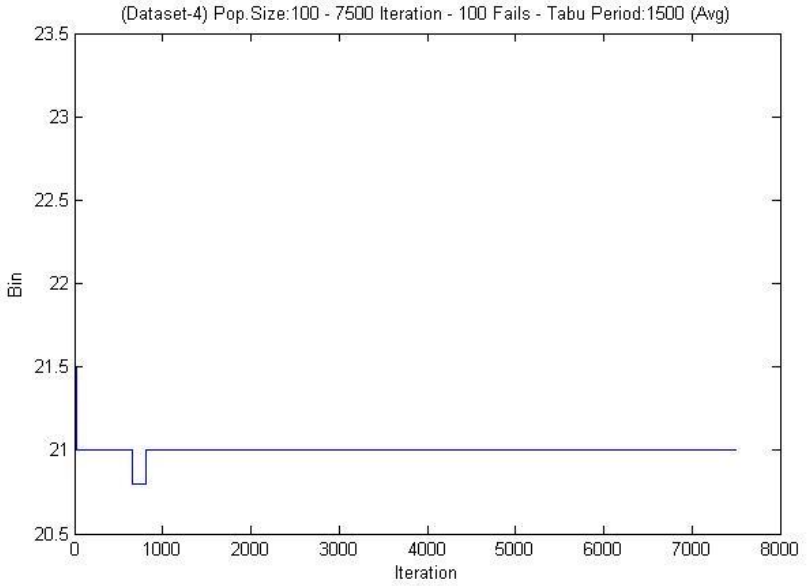

Fig. 62.A: Average Number of Bin for Table 19.B

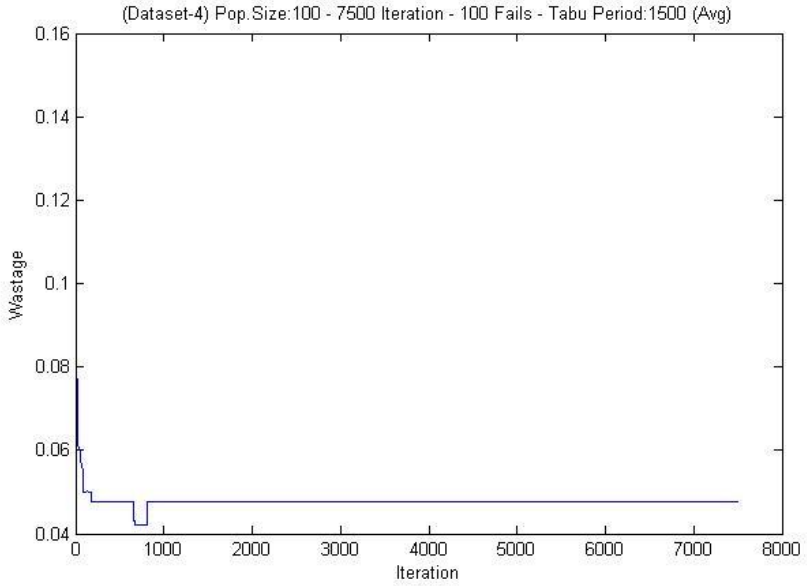

Fig. 62.B: Average Wastage for Table 19.B

Table-19.C: Results of MEABC Algorithm for Itemset-5 Group-9

Swarm:100 Iteration:7500 Max Number of Fail:100 Tabu Period:1500 Minimum Bin Usage Ratio:0.50 Group:9 Optimum Number of Bin:20																		
Test	1		2		3		4		5		OVERALL							
Time(sc)	462.9617		457.4456		470.7717		461.7659		438.9319		BIN				WASTE			
	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Best	No.Best	Mean	St. Dev.	Best	No.Best	Mean	St. Dev.
Best	21	0.0476	21	0.0476	20	0.0231	21	0.0476	21	0.0476	20	1	20.8	0.4472	0.0231	1	0.0427	0.0110
Mean	21.002	0.0478	21.001	0.0477	20.985	0.0473	21.002	0.0477	21.002	0.0477	20.985	1	20.998	0.0073	0.0473	1	0.0477	0.0002
St. Dev.	0.0516	0.0027	0.0365	0.0020	0.1363	0.0039	0.0554	0.0027	0.0516	0.0024	0.0365	1	0.0663	0.0398	0.0020	1	0.0027	0.0007

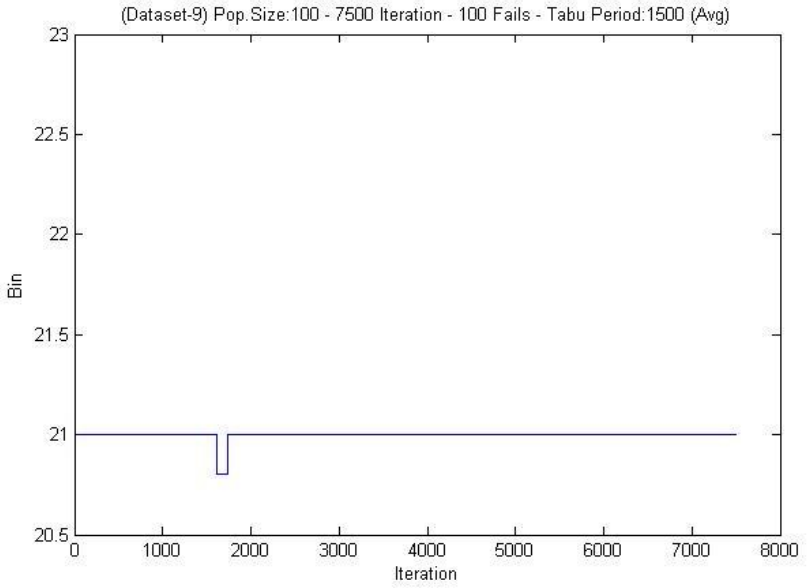

Fig. 63.A: Average Number of Bin for Table 19.C

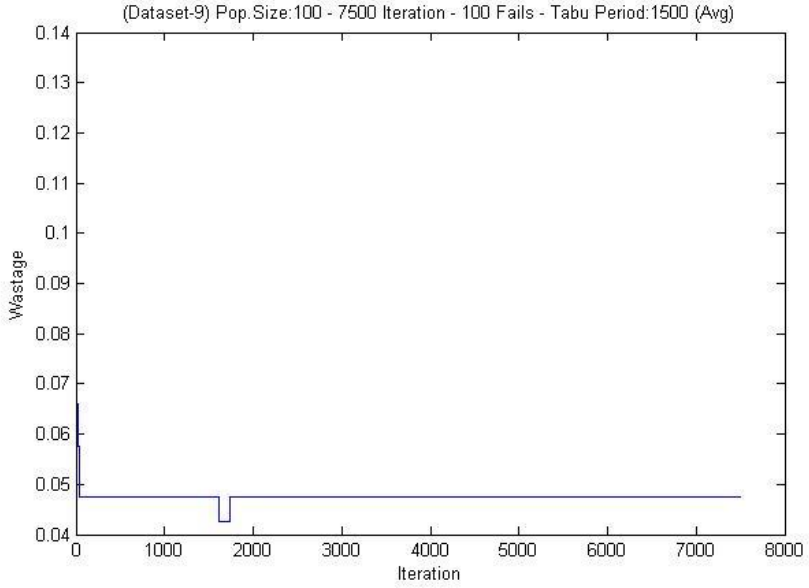

Fig. 63.B: Average Wastage for Table 19.C

Table-19.D: Results of MEABC Algorithm for Itemset-5 Group-15

Swarm:100 Iteration:7500 Max Number of Fail:100 Tabu Period:1500 Minimum Bin Usage Ratio:0.50 Group:15 Optimum Number of Bin:20																		
Test	1		2		3		4		5		OVERALL							
Time(sc)	478.2567		531.6818		441.1302		452.9791		446.3824		BIN				WASTE			
	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Best	No.Best	Mean	St. Dev.	Best	No.Best	Mean	St. Dev.
Best	20	0.0230	21	0.0476	21	0.0476	20	0.0237	21	0.0476	20	2	20.6	0.5477	0.0230	1	0.0379	0.0133
Mean	20.987	0.0474	21.002	0.0478	21.002	0.0478	20.986	0.0474	21.001	0.0478	20.986	1.0000	20.996	0.0084	0.0474	1.0000	0.0476	0.0002
St. Dev.	0.1310	0.0040	0.0600	0.0028	0.0622	0.0029	0.1393	0.0041	0.0447	0.0024	0.0447	1	0.0874	0.0442	0.0024	1	0.0033	0.0008

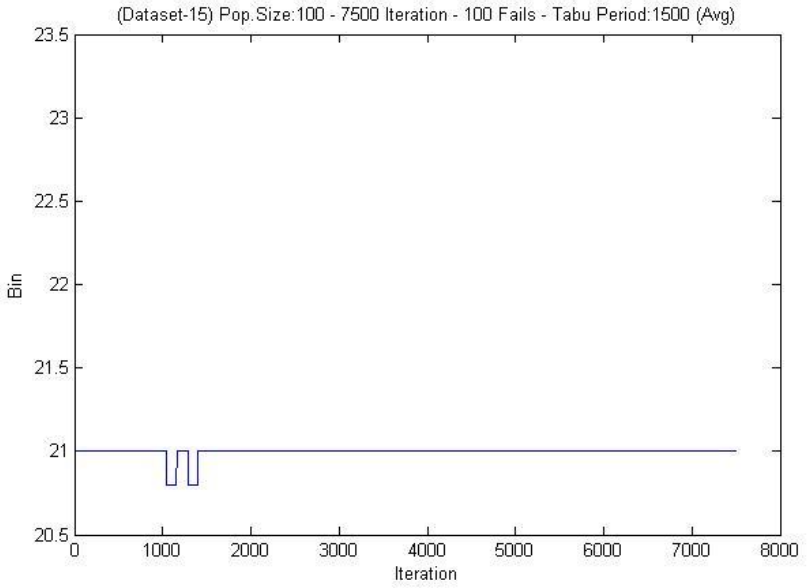

Fig. 64.A: Average Number of Bin for Table 19.D

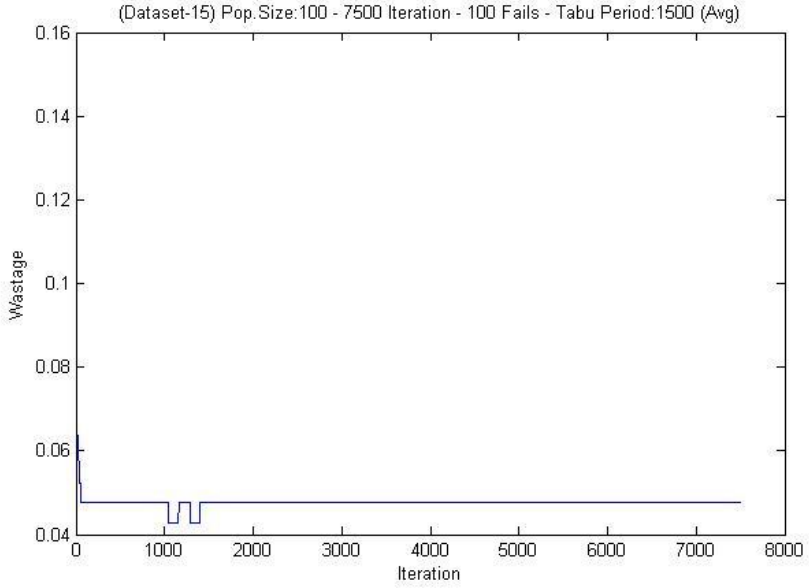

Fig. 64.B: Average Wastage for Table 19.D

Table-19.E: Results of MEABC Algorithm for Itemset-5 Group-18

Swarm:100 Iteration:7500 Max Number of Fail:100 Tabu Period:1500 Minimum Bin Usage Ratio:0.50 Group:18 Optimum Number of Bin:20																			
Test	1		2		3		4		5		OVERALL								
Time(sc)	472.2183		442.9414		442.5902		487.3755		458.3236		BIN				WASTE				
	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Best	No.Best	Mean	St. Dev.	Best	No.Best	Mean	St. Dev.
Best	21	0.0476	20	0.0239	21	0.0476	21	0.0476	21	0.0476	20	1	20.8	0.4472	0.0239	1	0.0429	0.0106
Mean	21.002	0.0478	20.983	0.0473	21.003	0.0478	21.003	0.0478	21.002	0.0478	20.983	1	20.999	0.0085	0.0473	1	0.0477	0.0002
St. Dev.	0.0632	0.0029	0.1442	0.0041	0.0682	0.0032	0.0621	0.0031	0.0516	0.0025	0.0516	1	0.0779	0.0376	0.0025	1	0.0032	0.0006

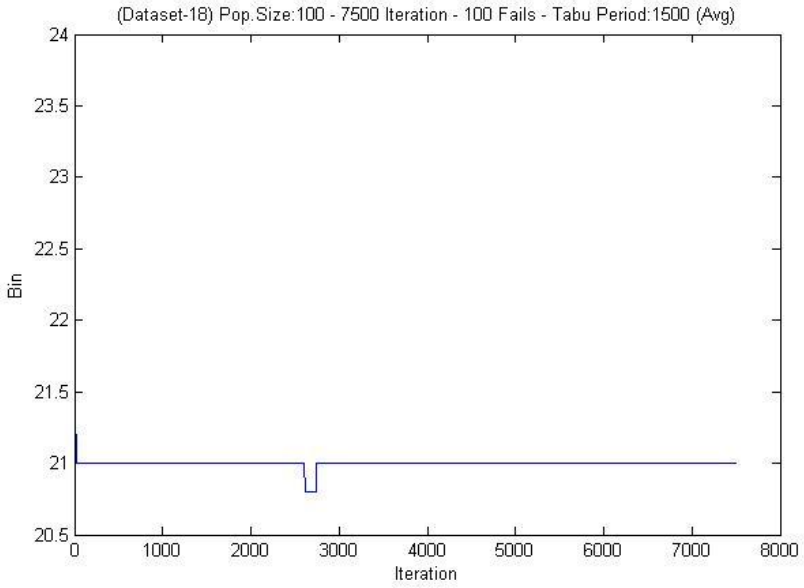

Fig. 65.A: Average Number of Bin for Table 19.E

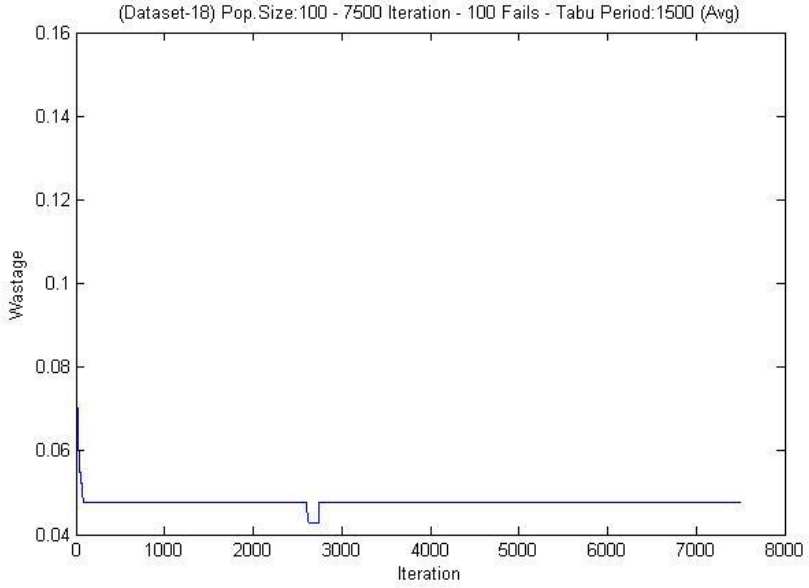

Fig. 65.B: Average Wastage for Table 19.E

Table-20.A: Results of MEABC Algorithm for Itemset-6 Group-2

Swarm:100 Iteration:7500 Max Number of Fail:100 Tabu Period:1500 Minimum Bin Usage Ratio:0.50 Group:2 Optimum Number of Bin:40																		
Test	1		2		3		4		5		OVERALL							
Time(sc)	1.08E+03		1.06E+03		1.05E+03		1.11E+03		1.05E+03		BIN				WASTE			
	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Best	No.Best	Mean	St. Dev.	Best	No.Best	Mean	St. Dev.
Best	41	0.0347	41	0.0335	41	0.0353	42	0.0476	41	0.0345	41	4	41.2	0.4472	0.0335	1	0.0371	0.0059
Mean	42.211	0.0535	42.003	0.0480	42.005	0.0478	42.015	0.0481	42.004	0.0479	42.003	1	42.047	0.0913	0.0478	1	0.0491	0.0025
St. Dev.	0.5227	0.0107	0.2414	0.0050	0.2016	0.0043	0.2124	0.0047	0.2318	0.0048	0.2016	1	0.2820	0.1355	0.0043	1	0.0059	0.0027

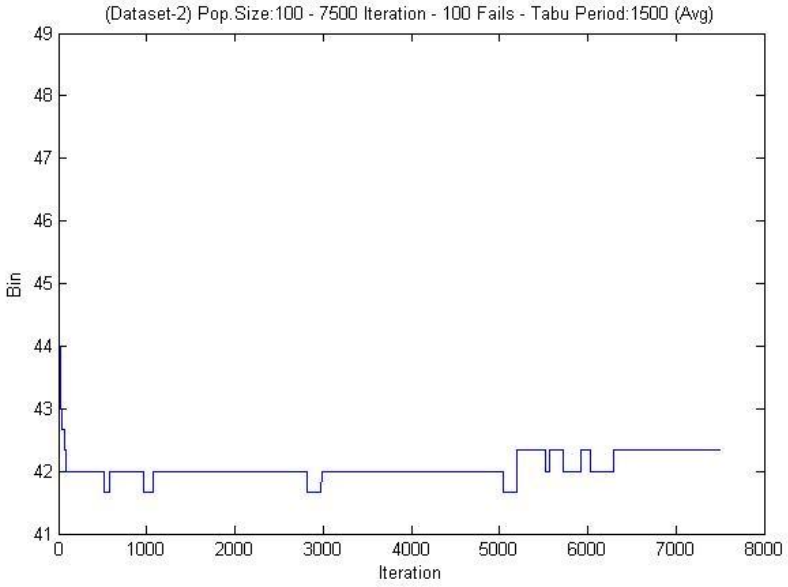

Fig. 66.A: Average Number of Bin for Table 20.A

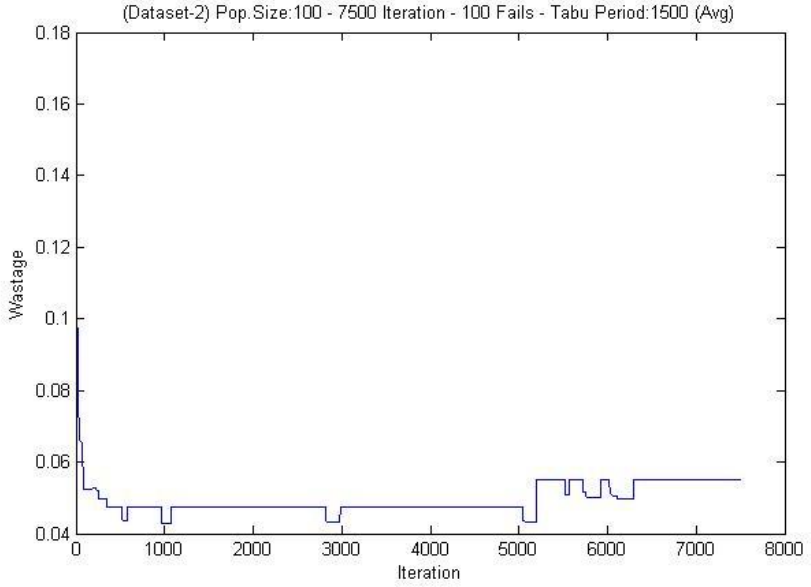

Fig. 66.B: Average Wastage for Table 20.A

Table-20.B: Results of MEABC Algorithm for Itemset-6 Group-3

Swarm:100 Iteration:7500 Max Number of Fail:100 Tabu Period:1500 Minimum Bin Usage Ratio:0.50 Group:3 Optimum Number of Bin:40																		
Test	1		2		3		4		5		OVERALL							
Time(sc)	1.06E+03		1.06E+03		1.06E+03		1.06E+03		1.05E+03		BIN				WASTE			
	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Best	No.Best	Mean	St. Dev.	Best	No.Best	Mean	St. Dev.
Best	42	0.0476	42	0.0536	42	0.0476	42	0.0476	42	0.0537	42	5	42	0.0000	0.0476	1	0.0500	0.0033
Mean	42.013	0.0481	42.813	0.0671	42.019	0.0483	42.014	0.0481	42.79	0.0668	42.013	1	42.33	0.4306	0.0481	1	0.0557	0.0103
St. Dev.	0.1872	0.0042	0.4220	0.0066	0.2143	0.0048	0.1982	0.0044	0.4416	0.0068	0.1872	1	0.2926	0.1276	0.0042	1	0.0054	0.0012

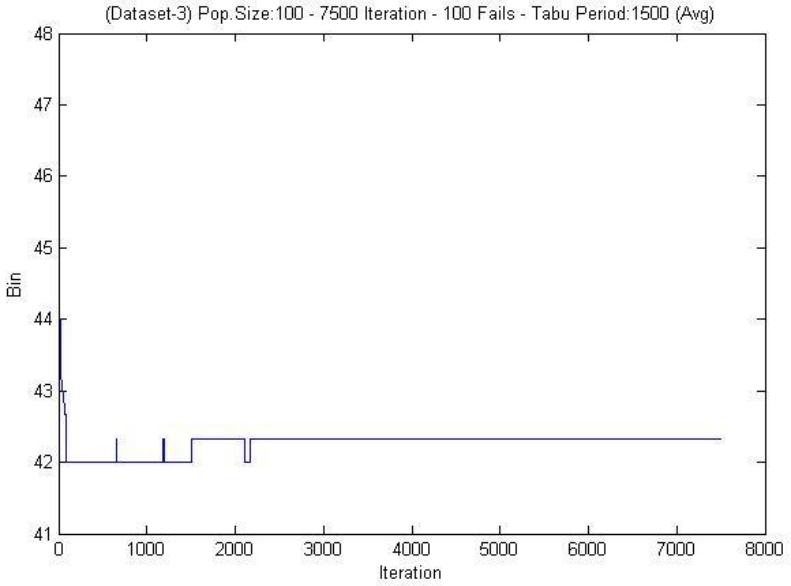

Fig. 67.A: Average Number of Bin for Table 20.B

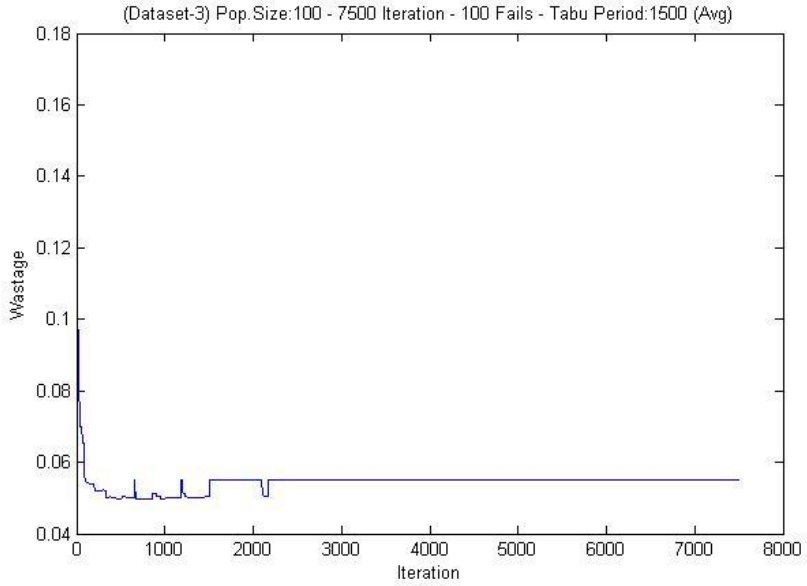

Fig. 67.B: Average Wastage for Table 20.B

Table-20.C: Results of MEABC Algorithm for Itemset-6 Group-5

Swarm:100 Iteration:7500 Max Number of Fail:100 Tabu Period:1500 Minimum Bin Usage Ratio:0.50 Group:5 Optimum Number of Bin:40																			
Test	1		2		3		4		5		OVERALL								
Time(sc)	1.06E+03		1.05E+03		1.17E+03		1.06E+03		1.12E+03		BIN				WASTE				
	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Best	No.Best	Mean	St. Dev.	Best	No.Best	Mean	St. Dev.	
Best	41	0.0338	42	0.0476	42	0.0476	42	0.0476	42	0.0476	41	1	41.8	0.4472	0.0338	1	0.0448	0.0062	
Mean	42.814	0.0664	42.017	0.0482	42.016	0.0491	42.014	0.0481	42.015	0.0481	42.014	1	42.175	0.3573	0.0481	1	0.0520	0.0081	
St. Dev.	0.4584	0.0087	0.2056	0.0048	0.2114	0.0053	0.1982	0.0044	0.2124	0.0047	0.1982	1	0.2572	0.1126	0.0044	1	0.0056	0.0018	

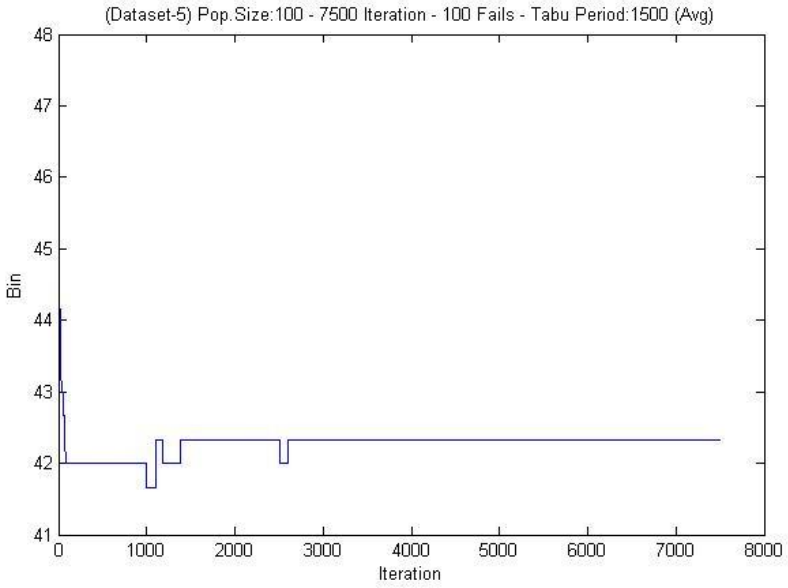

Fig. 68.A: Average Number of Bin for Table 20.C

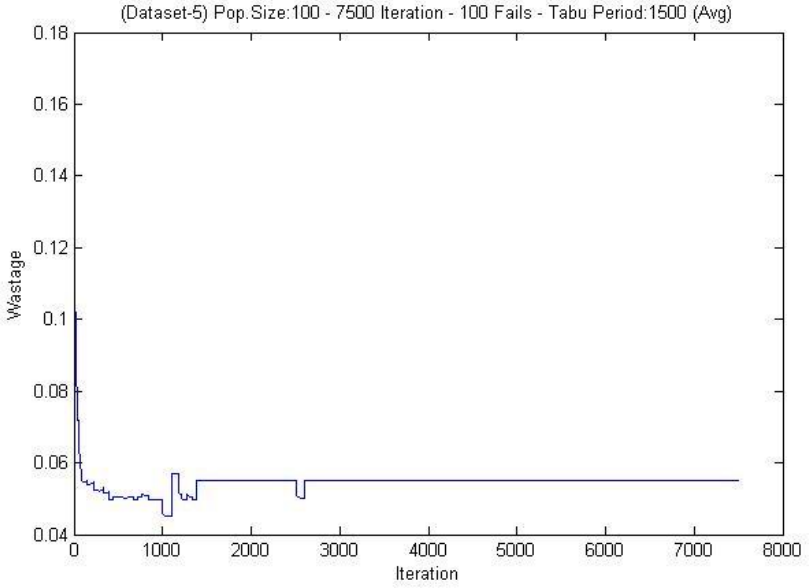

Fig. 68.B: Average Wastage for Table 20.C

Table-20.D: Results of MEABC Algorithm for Itemset-6 Group-14

Swarm:100 Iteration:7500 Max Number of Fail:100 Tabu Period:1500 Minimum Bin Usage Ratio:0.50 Group:14 Optimum Number of Bin:40																			
Test	1		2		3		4		5		OVERALL								
Time(sc)	1.05E+03		1.11E+03		1.05E+03		1.17E+03		1.06E+03		BIN				WASTE				
	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Best	No.Best	Mean	St. Dev.	Best	No.Best	Mean	St. Dev.	
Best	41	0.0345	42	0.0476	41	0.0342	42	0.0537	41	0.0347	41	3	41.4	0.5477	0.0342	1	0.0409	0.0091	
Mean	42.004	0.0479	42.014	0.0481	41.991	0.0477	42.79	0.0668	42.211	0.0535	41.991	1	42.202	0.3408	0.0477	1	0.0528	0.0082	
St. Dev.	0.2318	0.0048	0.1982	0.0044	0.2632	0.0051	0.4416	0.0068	0.5227	0.0107	0.1982	1	0.3315	0.1423	0.0044	1	0.0064	0.0026	

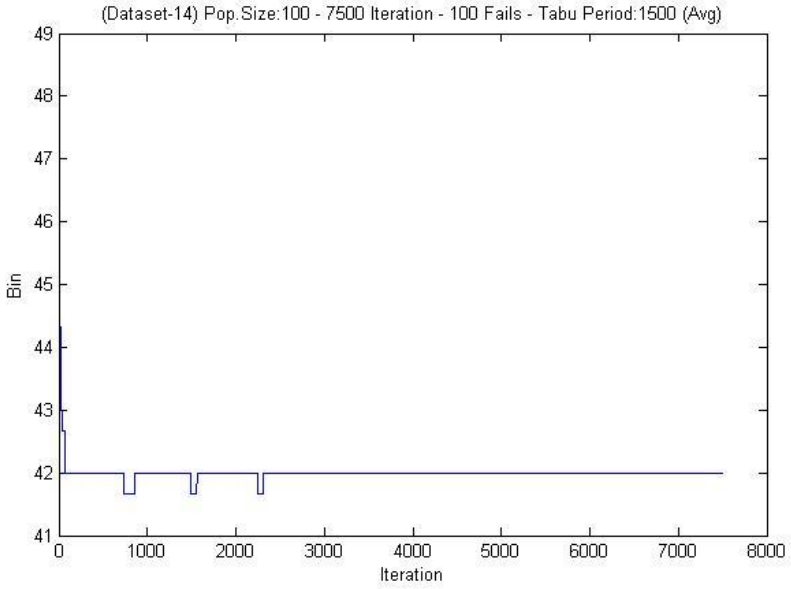

Fig. 69.A: Average Number of Bin for Table 20.D

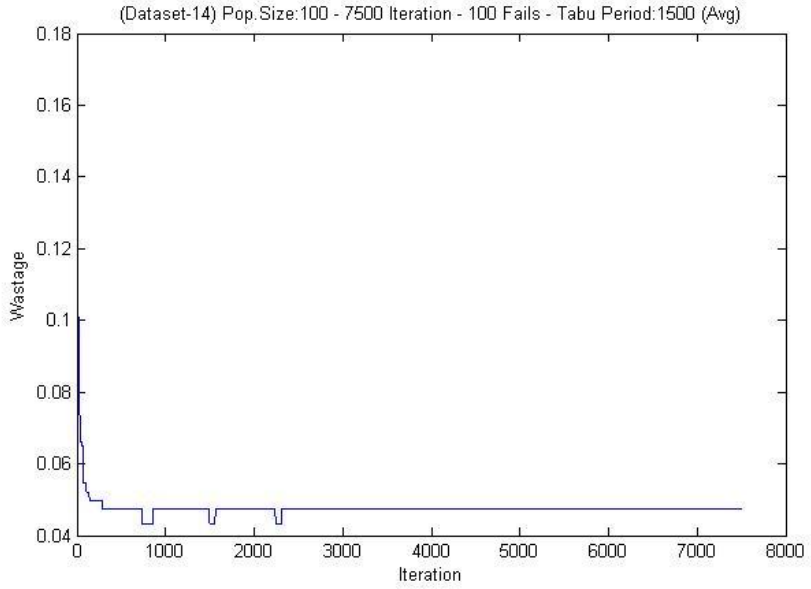

Fig. 69.B: Average Wastage for Table 20.D

Table-20.E: Results of MEABC Algorithm for Itemset-6 Group-18

Swarm:100 Iteration:7500 Max Number of Fail:100 Tabu Period:1500 Minimum Bin Usage Ratio:0.50 Group:18 Optimum Number of Bin:40																			
Test	1		2		3		4		5		OVERALL								
Time(sc)	1.12E+03		1.10E+03		1.14E+03		1.06E+03		1.08E+03		BIN				WASTE				
	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Best	No.Best	Mean	St. Dev.	Best	No.Best	Mean	St. Dev.	
Best	42	0.0476	42	0.0537	42	0.0476	42	0.0536	42	0.0536	42	5	42	0.0000	0.0476	1	0.0512	0.0033	
Mean	42.015	0.0481	42.79	0.0668	42.016	0.0484	42.813	0.0671	42.813	0.0671	42.015	1	42.489	0.4327	0.0481	1	0.0595	0.0103	
St. Dev.	0.2124	0.0047	0.4416	0.0068	0.2245	0.0052	0.4220	0.0066	0.4220	0.0066	0.2124	1	0.3445	0.1154	0.0047	1	0.0060	0.0010	

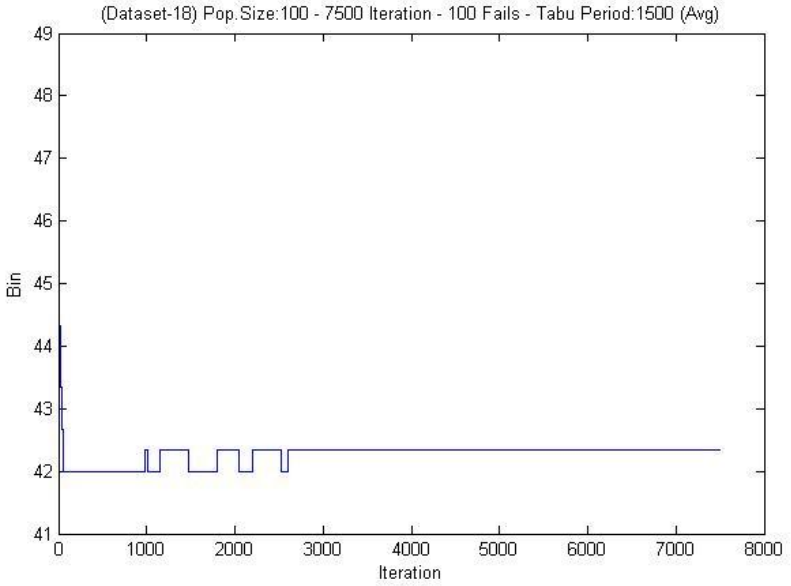

Fig. 70.A: Average Number of Bin for Table 20.E

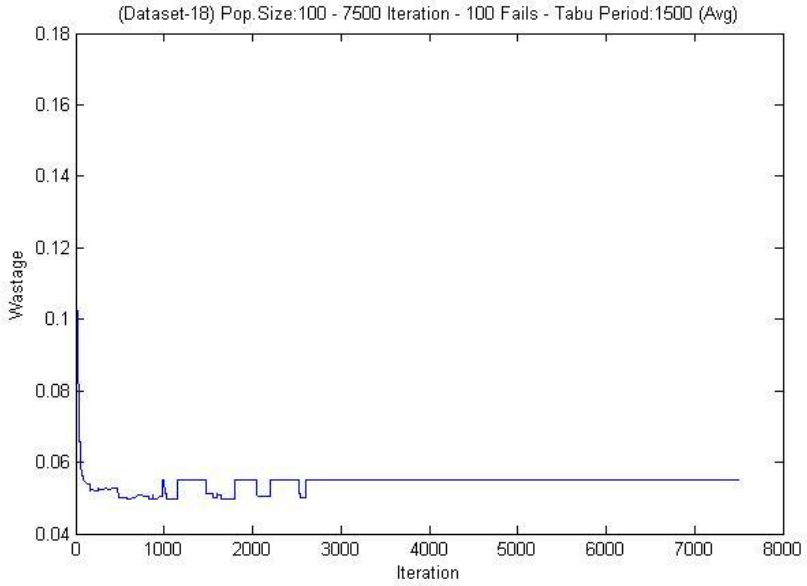

Fig. 70.B: Average Wastage for Table 20.E

Table-21.A: Results of MEABC Algorithm for Itemset-7 Group-1

Swarm:100 Iteration:7500 Max Number of Fail:100 Tabu Period:1500 Minimum Bin Usage Ratio:0.50 Group:1 Optimum Number of Bin:83																		
Test	1		2		3		4		5		OVERALL							
Time(sc)	1.99E+03		2.00E+03		1.85E+03		1.96E+03		1.95E+03		BIN				WASTE			
	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Best	No.Best	Mean	St. Dev.	Best	No.Best	Mean	St. Dev.
Best	88	0.0568	87	0.0510	88	0.0574	88	0.0578	87	0.0584	87	2	87.6	0.5477	0.0510	1	0.0563	0.0030
Mean	88.056	0.0576	88.043	0.0574	88.075	0.0587	88.063	0.0579	88.044	0.0582	88.043	1	88.056	0.0136	0.0574	1	0.0580	0.0005
St. Dev.	0.5613	0.0057	0.6108	0.0061	0.5572	0.0057	0.5698	0.0058	0.6188	0.0060	0.5572	1	0.5836	0.0290	0.0057	1	0.0059	0.0002

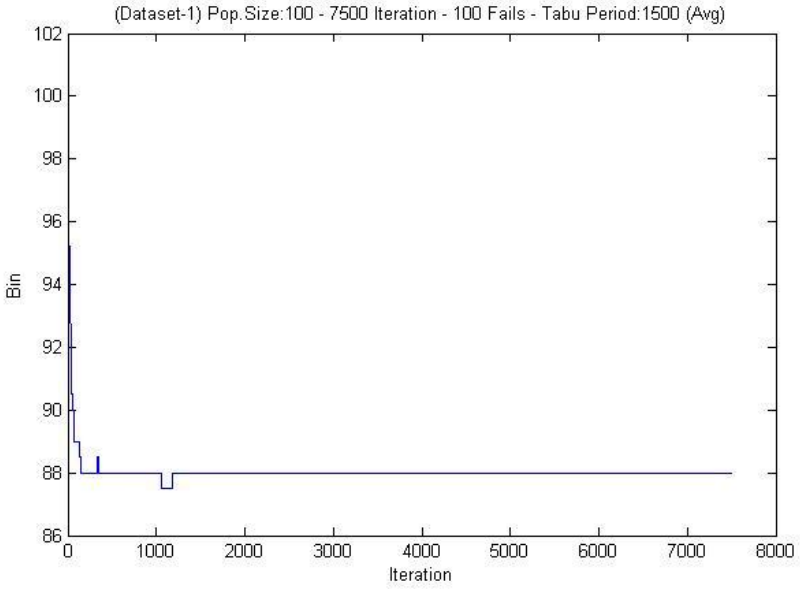

Fig. 71.A: Average Number of Bin for Table 21.A

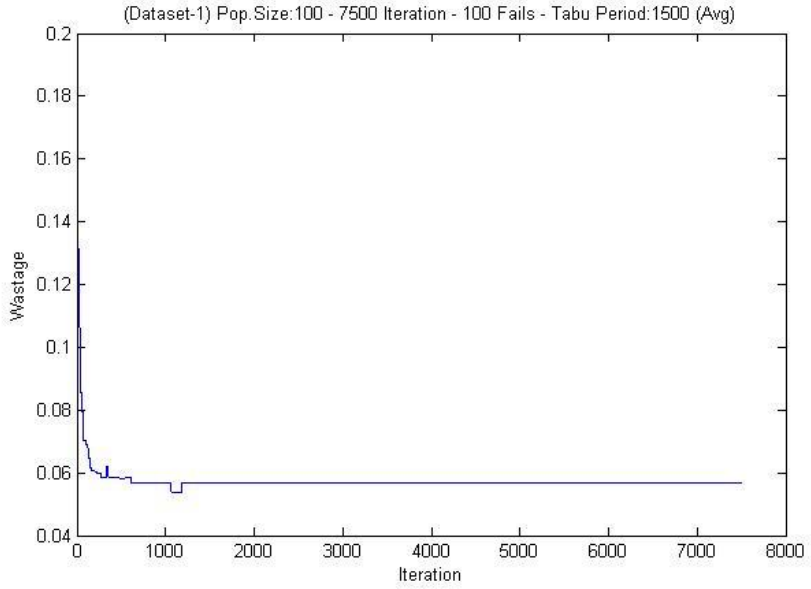

Fig. 71.B: Average Wastage for Table 21.A

Table-21.B: Results of MEABC Algorithm for Itemset-7 Group-4

Swarm:100 Iteration:7500 Max Number of Fail:100 Tabu Period:1500 Minimum Bin Usage Ratio:0.50 Group:4 Optimum Number of Bin:83																			
Test	1		2		3		4		5		OVERALL								
Time(sc)	1.94E+03		1.81E+03		1.78E+03		1.83E+03		1.97E+03		BIN				WASTE				
	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Best	No.Best	Mean	St. Dev.	Best	No.Best	Mean	St. Dev.
Best	87	0.0497	87	0.0498	87	0.0498	87	0.0498	87	0.0498	87	5	87	0.0000	0.0497	1	0.0498	0.0001
Mean	88.018	0.0573	88.088	0.0583	88.088	0.0583	88.088	0.0583	88.088	0.0583	88.018	1	88.074	0.0313	0.0573	1	0.0581	0.0004
St. Dev.	0.6339	0.0062	0.6732	0.0067	0.6732	0.0067	0.6732	0.0067	0.6732	0.0067	0.6339	1	0.6653	0.0176	0.0062	1	0.0066	0.0002

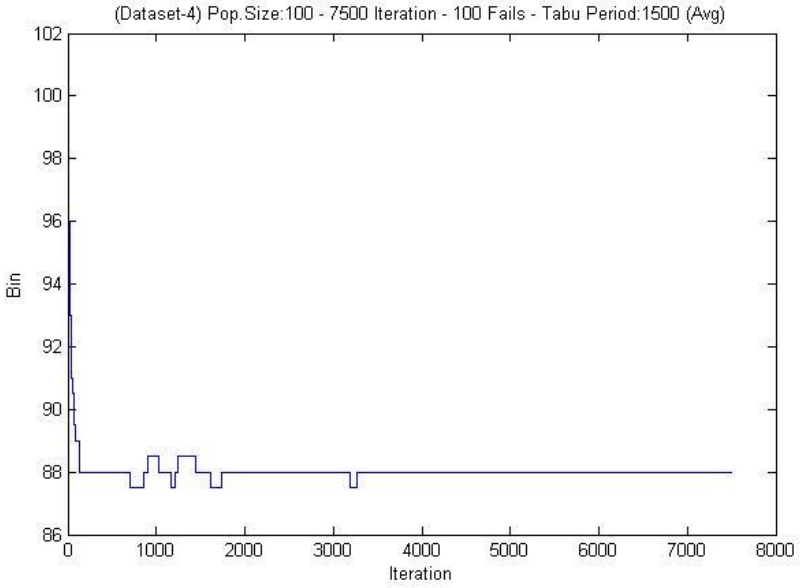

Fig. 72.A: Average Number of Bin for Table 21.B

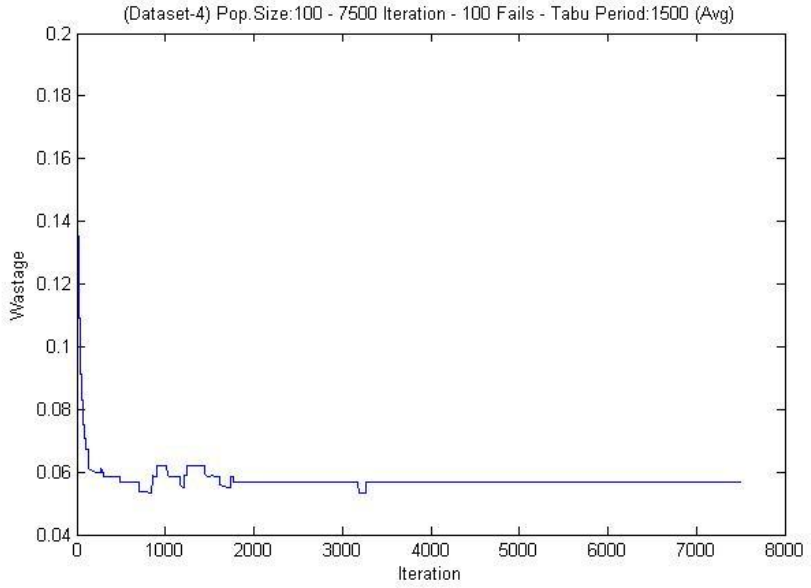

Fig. 72.B: Average Wastage for Table 21.B

Table-21.C: Results of MEABC Algorithm for Itemset-7 Group-9

Swarm:100 Iteration:7500 Max Number of Fail:100 Tabu Period:1500 Minimum Bin Usage Ratio:0.50 Group:9 Optimum Number of Bin:83																			
Test	1		2		3		4		5		OVERALL								
Time(sc)	1.99E+03		1.89E+03		1.95E+03		1.83E+03		1.95E+03		BIN				WASTE				
	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Best	No.Best	Mean	St. Dev.	Best	No.Best	Mean	St. Dev.
Best	87	0.0493	87	0.0495	87	0.0495	87	0.0495	87	0.0495	87	5	87	0.0000	0.0493	1	0.0495	0.0001
Mean	88.033	0.0573	88.023	0.0573	88.023	0.0573	88.023	0.0573	88.023	0.0573	88.023	4	88.025	0.0047	0.0573	1	0.0573	0.0000
St. Dev.	0.6448	0.0063	0.6800	0.0066	0.6800	0.0066	0.6800	0.0066	0.6800	0.0066	0.6448	1	0.6729	0.0157	0.0063	1	0.0065	0.0001

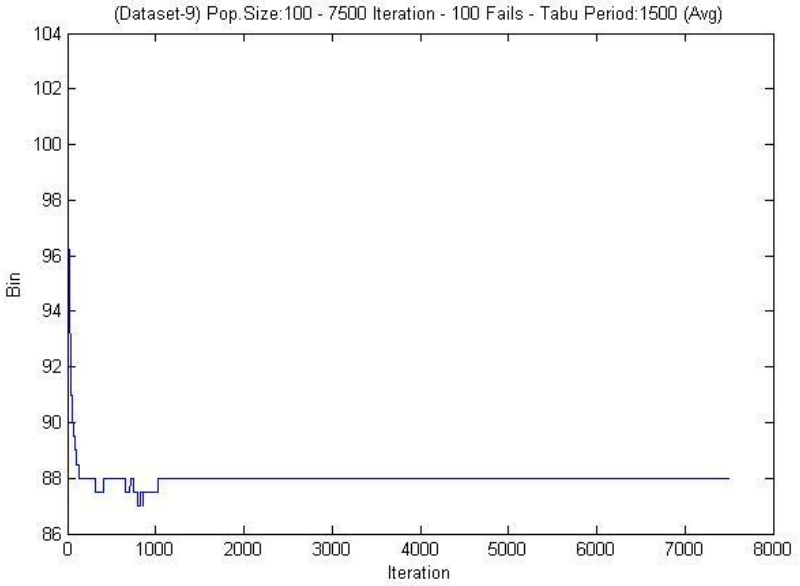

Fig. 73.A: Average Number of Bin for Table 21.C

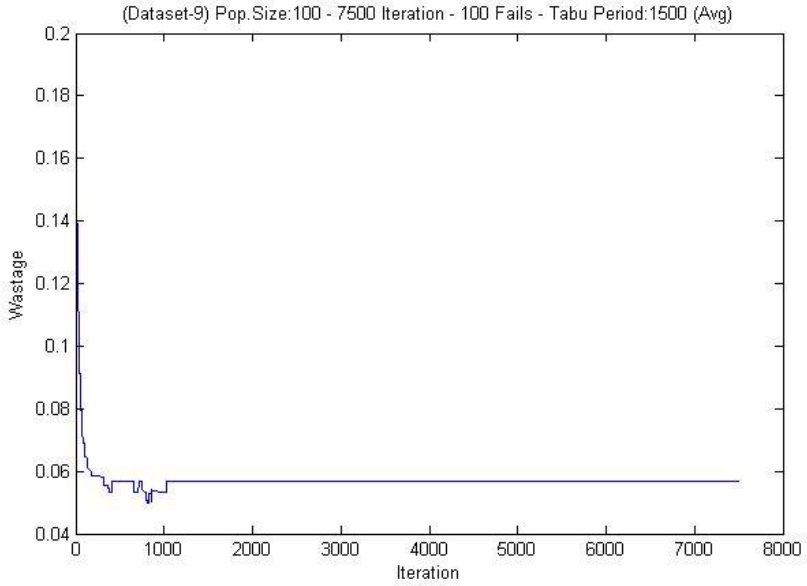

Fig. 73.B: Average Wastage for Table 21.C

Table-21.D: Results of MEABC Algorithm for Itemset-7 Group-11

Swarm:100 Iteration:7500 Max Number of Fail:100 Tabu Period:1500 Minimum Bin Usage Ratio:0.50 Group:11 Optimum Number of Bin:83																			
Test	1		2		3		4		5		OVERALL								
Time(sc)	1.88E+03		1.73E+03		1.97E+03		1.81E+03		1.94E+03		BIN				WASTE				
	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Best	No.Best	Mean	St. Dev.	Best	No.Best	Mean	St. Dev.
Best	87	0.0495	87	0.0460	87	0.0495	87	0.0495	87	0.0495	87	5	87	0.0000	0.0460	1	0.0488	0.0016
Mean	88.048	0.0575	87.139	0.0478	88.048	0.0575	88.048	0.0575	88.048	0.0575	87.139	1	87.866	0.4068	0.0478	1	0.0555	0.0043
St. Dev.	0.6266	0.0063	0.7371	0.0079	0.6266	0.0063	0.6266	0.0063	0.6266	0.0063	0.6266	4	0.6487	0.0494	0.0063	4	0.0066	0.0007

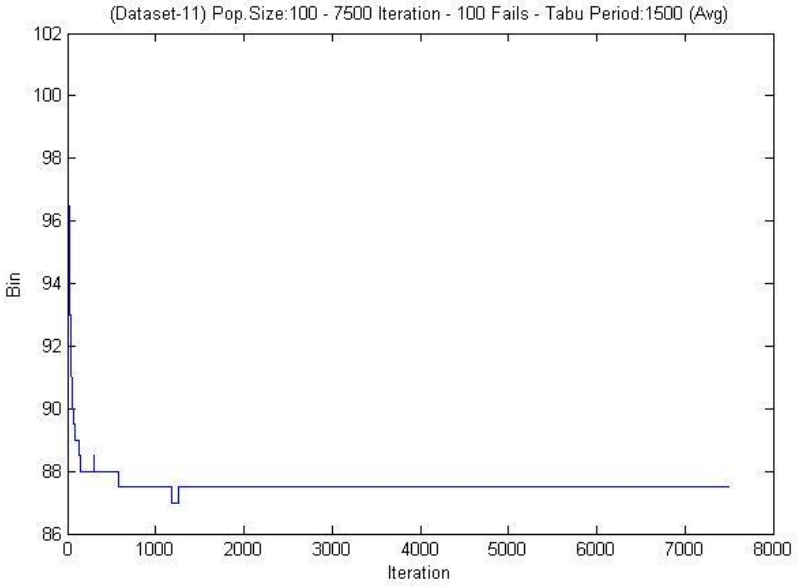

Fig. 74.A: Average Number of Bin for Table 21.D

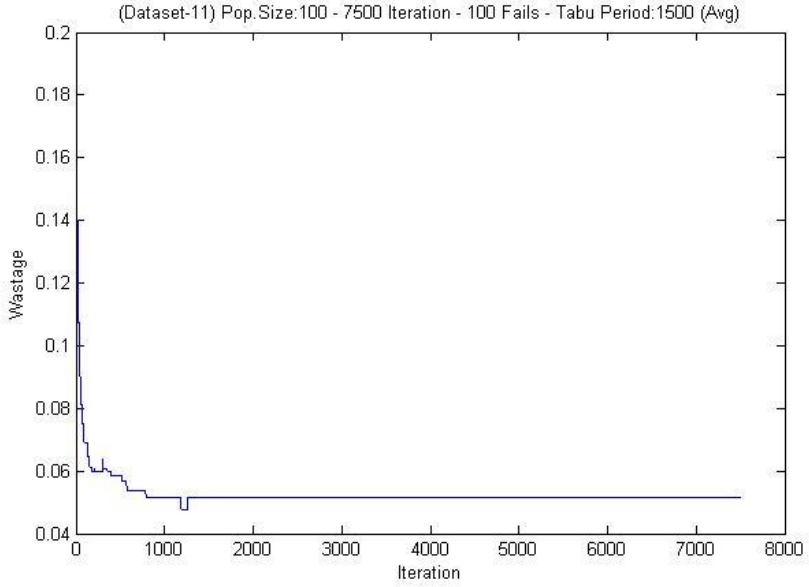

Fig. 74.B: Average Wastage for Table 21.D

Table-21.E: Results of MEABC Algorithm for Itemset-7 Group-15

Swarm:100 Iteration:7500 Max Number of Fail:100 Tabu Period:1500 Minimum Bin Usage Ratio:0.50 Group:15 Optimum Number of Bin:83																			
Test	1		2		3		4		5		OVERALL								
Time(sc)	1.83E+03		1.95E+03		1.96E+03		2.00E+03		1.73E+03		BIN				WASTE				
	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Bin	Waste	Best	No.Best	Mean	St. Dev.	Best	No.Best	Mean	St. Dev.
Best	87	0.0498	87	0.0490	87	0.0498	87	0.0493	87	0.0510	87	5	87	0.0000	0.0490	1	0.0498	0.0008
Mean	87.977	0.0569	87.995	0.0570	87.977	0.0569	88.033	0.0573	88.043	0.0574	87.977	2	88.005	0.0312	0.0569	2	0.0571	0.0002
St. Dev.	0.6660	0.0063	0.6699	0.0064	0.6660	0.0063	0.6448	0.0063	0.6108	0.0061	0.6108	1	0.6515	0.0248	0.0061	1	0.0063	0.0001

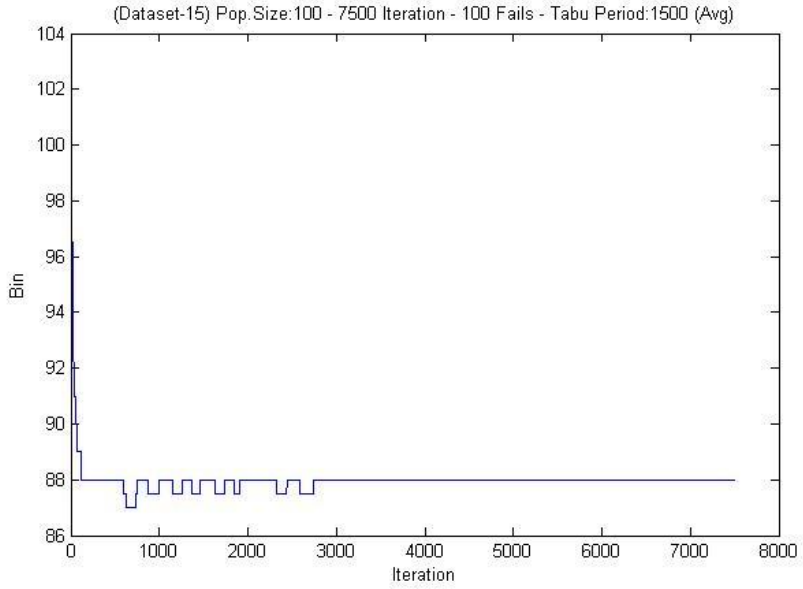

Fig. 75.A: Average Number of Bin for Table 21.E

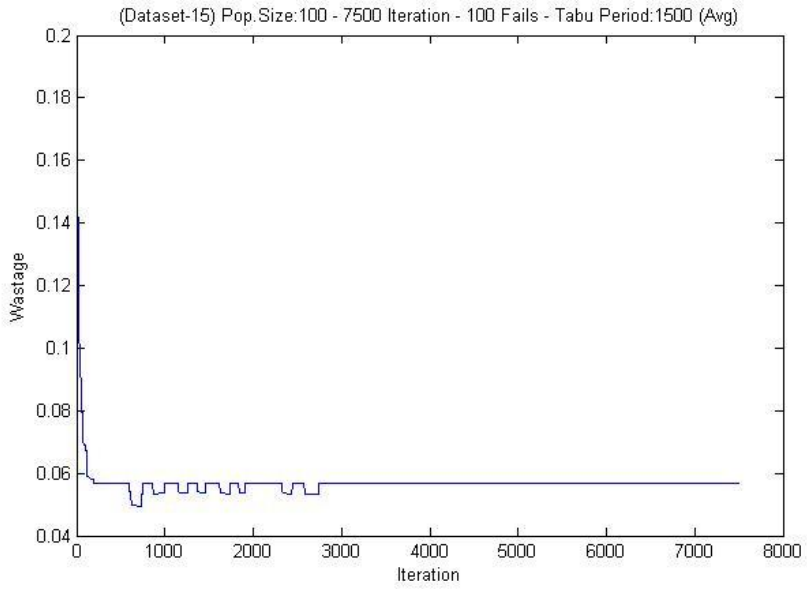

Fig. 75.B: Average Wastage for Table 21.E

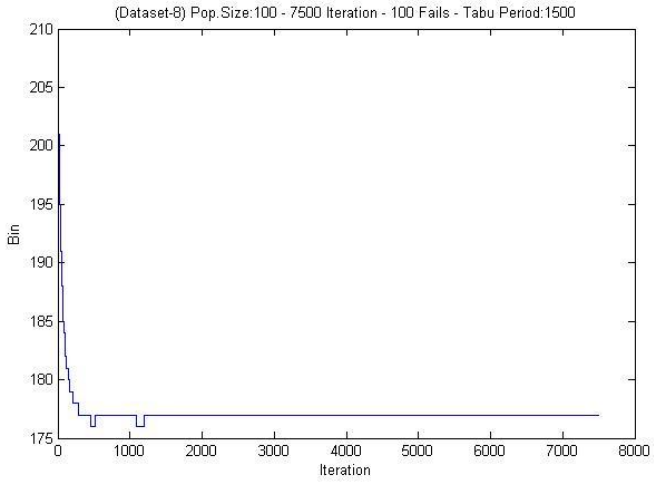

Fig. 76.A: MEABC Results for Number of Bin for Group-8 in Table-16

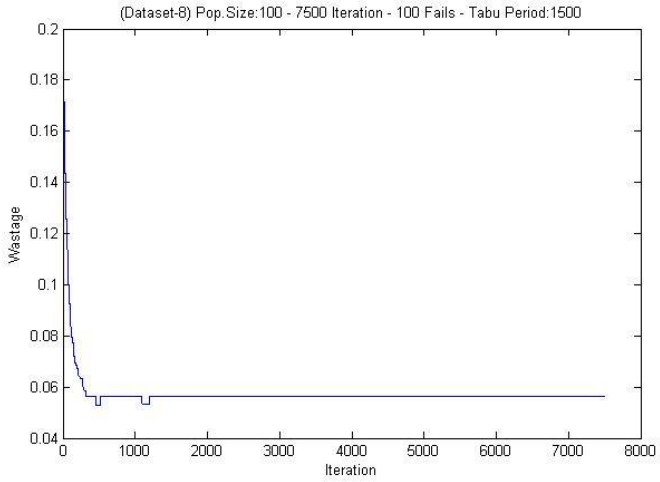

Fig. 76.B: MEABC Results for Wastage for Group-8 in Table-16

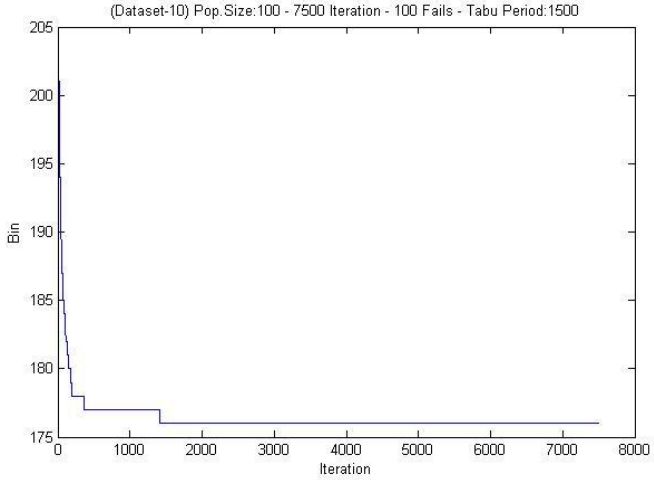

Fig. 77.A: MEABC Results for Number of Bin for Group-10 in Table-16

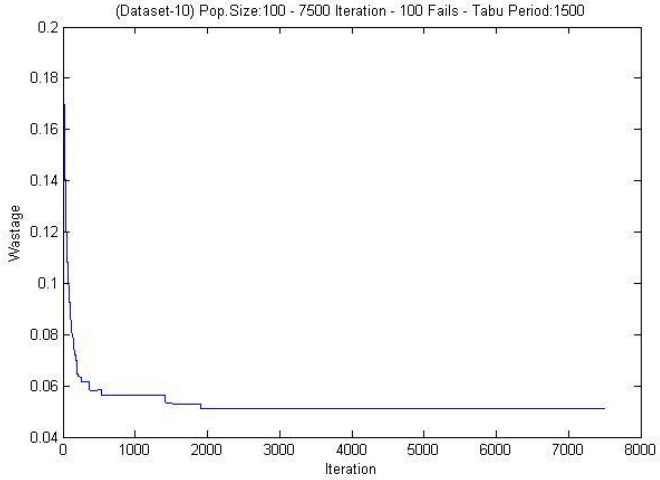

Fig. 77.B: MEABC Results for Wastage for Group-10 in Table-16

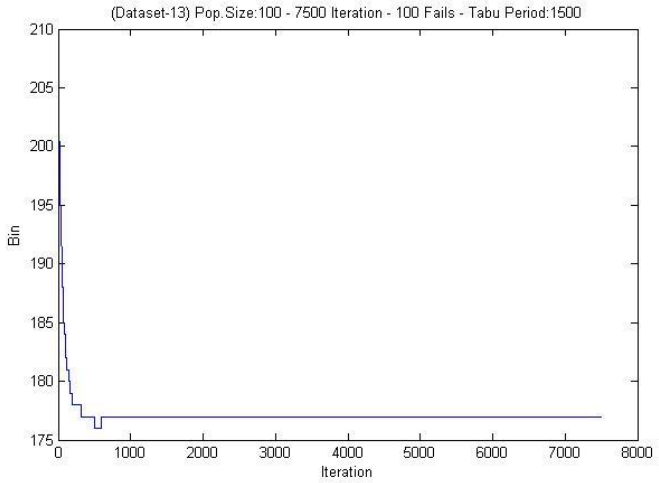

Fig. 78.A: MEABC Results for Number of Bin for Group-13 in Table-16

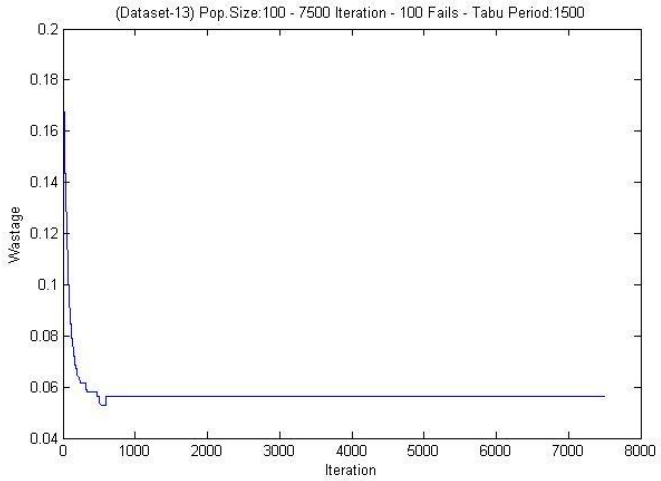

Fig. 78.B: MEABC Results for Wastage for Group-13 in Table-16

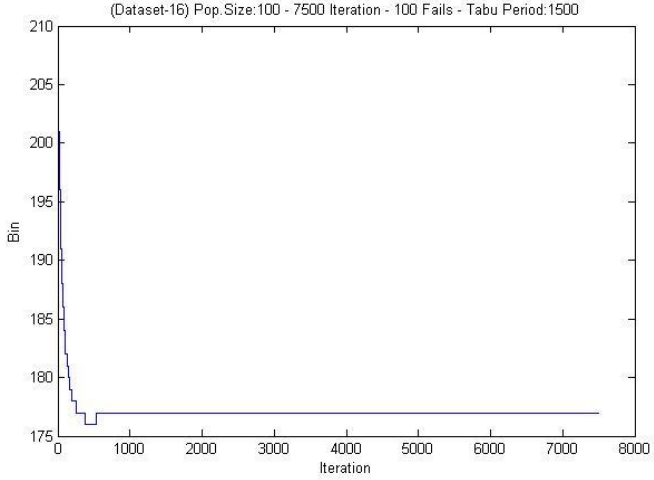

Fig. 79.A: MEABC Results for Number of Bin for Group-16 in Table-16

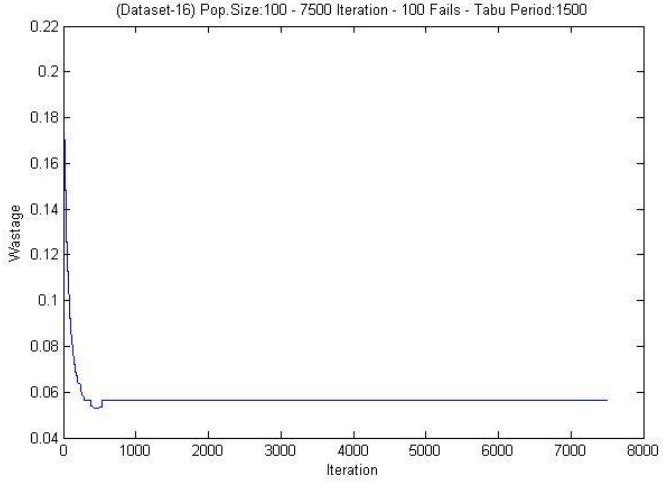

Fig. 79.B: MEABC Results for Wastage for Group-16 in Table-16

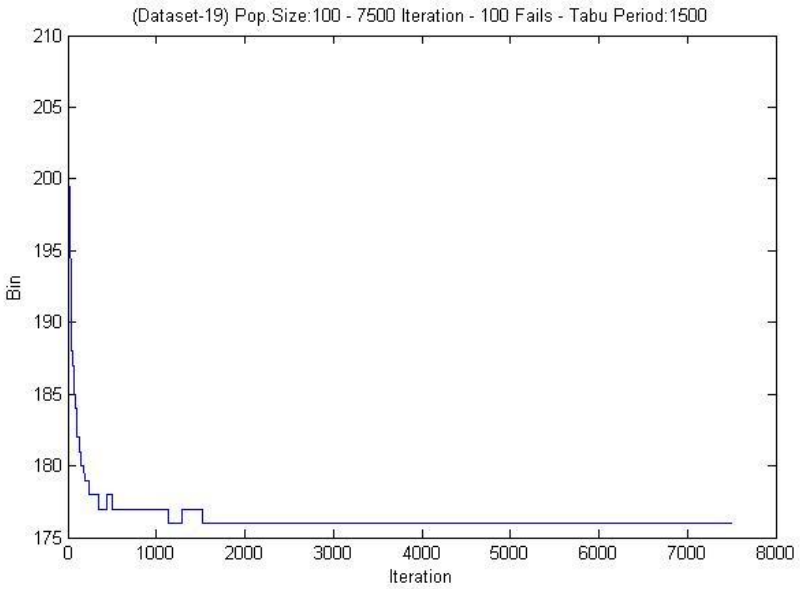

Fig. 80.A: MEABC Results for Number of Bin for Group-19 in Table-16

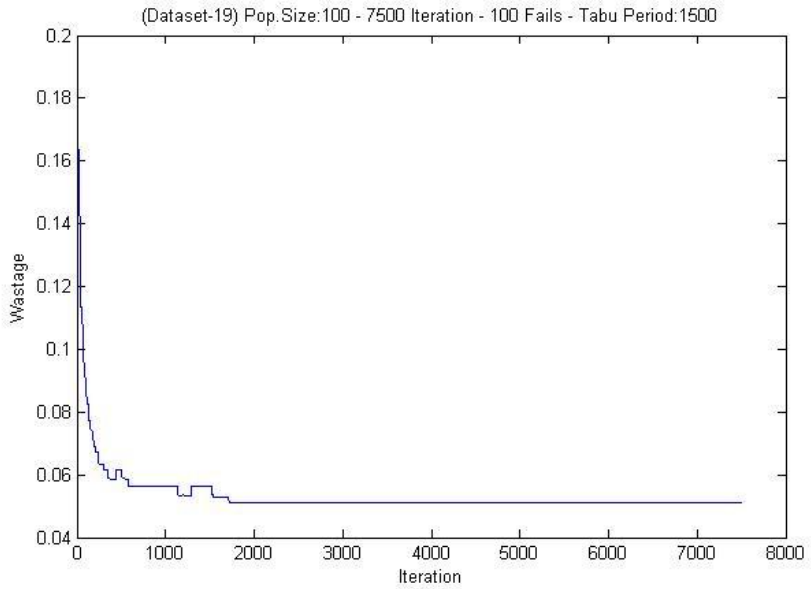

Fig. 80.B: MEABC Results for Wastage for Group-19 in Table-16